THREE ESSAYS ON BRAZILIAN SOCIAL SECURITY POLICIES, EDUCATION AND LABOR MARKET

BY

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DISSERTATION

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Abstract

The main purpose of this research is to analyze the impact of different public policies on the Brazilian labor market using rigorous econometric techniques to study the Brazilian public sector. A clear theoretical and empirical comprehension is crucial when designing policies to mitigate social problems, as well-intentioned policies may exacerbate the original problems if they are not correctly designed. The first chapter of this research studies the impact on the labor market of a public Social Security system that provides disability insurance benefits. This study searches for possible worker incentives to leave the labor force temporarily by comparing workers with the same health. Additionally, this study analyzes the extent to which workers with poor health continue to work because they lack social security coverage. I analyze the Brazilian disability insurance system, searching for possible incentives created by the system. The empirical analysis will be based on the system's rule that only formal-economy workers are covered, taking advantage of the considerable proportion of workers in informal jobs in the Brazilian labor market; however, as formalized workers may differ in other ways from workers in the informal sector, the approach will account for this heterogeneity. The results reveal that workers in the formal sector are more likely to take leave, even after controlling for health. This difference reveals the effects of such social protection systems on the labor market and, at the same time, reveals the inequality in opportunities faced by informal-sector workers. Moreover, as having a formal job does not affect workers' behavior when they have health problems, significant differences in the number of workers that take leave in the formal and informal sectors are not explained by differences in health status among these workers. The second chapter of this research studies the effect of a series of changes to the Brazilian old-age pension on child labor and school enrollment. Child labor is still a considerable problem in Brazilian society. This article analyzes the impact of the 1991 reform of the Brazilian rural pension system on child labor, literacy and school attendance. The 1991 social-security reform represents a good opportunity to investigate how income is allocated between household members because the reform generated an exogenous income shock: it decreased the minimum age for old-age pension eligibility and substantially increased the value of the minimum benefit. A significant proportion of Brazilian households, especially in rural areas, are composed of a mix of adults, children and elderly family members. Therefore, any changes in social-security benefits and eligibility rules may affect not only the beneficiaries but the other household members, as well. The results reveal an improvement in the educational attainments of children living with eligible males. Moreover, eligible females helped their grandchildren to leave the labor market in cases of child labor and facilitated their granddaughters' educations. The analysis of the impact on different socioeconomic levels shows that the impacts are concentrated in the lowest socioeconomic quintile. In contrast to what is found in the literature, our estimates suggest that men dedicate their additional income to their granddaughters' educations. One possible explanation is that men and women have different bargaining powers inside the family. There is evidence that the presence of female heads of household explain why eligible females appear to favor their granddaughter's education and to favor their grandsons in cases of child labor. The third chapter recognizes the importance of education to the future of the children's performance in the labor market; therefore, this

study analyzes the impact of teacher quality on children's school performance. The reform of the public education system has played a major role in policy debates in Brazil over the last several years, especially after the universalization of standardized student-achievement evaluations. The disappointing performance of students on language and mathematics tests and the gap between students from public and private schools on most measures of academic achievement are source of concern to parents and policymakers, increasing the pressure to restructure the entire system. Nearly everyone involved in education recognizes the importance of teacher quality to student achievement; however, little is known about how teachers affect different kinds of students. This lack of knowledge is especially worrying when the public school system implements accountability programs, using student achievement in teacher assessments and putting pressure for achievement-related accountability on individual teachers and schools. The measure of the impact of teacher quality on students is not straightforward, as we cannot simply compare groups of students from different teachers. Aside from teacher quality, the school performance of a group of students would depend on (i) the starting knowledge levels of students, (ii) their endowments (abilities and family backgrounds), and (iii) the teacher's working conditions (for example, the school's infrastructure). Therefore, the objective of this empirical analysis is to obtain estimates of differences in teacher contributions to student learning that account for the major sources of possible confounding from student heterogeneity and teacher assignment practices. The results reveal that low-achieving students exposed to better-quality teachers would expect to achieve higher standard deviations higher in Portuguese and mathematics test-score performances. At the same time, high achieving students have Portuguese and mathematics scores increased when exposed to better quality teachers; however, such impact represents a larger proportion of the average test score gains for high-achieving students. Moreover, if we analyze the impact of teachers on different students inside the same classroom, we also observe that students in the top of the test score distribution benefit more from better quality teachers.

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PREFACE

The main purpose of this research is to analyze the impact of different public policies on the Brazilian labor market using rigorous econometric techniques to study the Brazilian public sector. A clear theoretical and empirical comprehension is crucial when designing policies to mitigate social problems, as well-intentioned policies may exacerbate the original problems if they are not correctly designed.

The first part of the research analyzes the impact of certain characteristics of Social Security on various aspects of the Brazilian labor market. An understanding of the worker incentives created by Social Security benefits is critical to improving the design of the system. Moreover, knowledge of any positive externality created by Social Security benefits is essential to a complete understanding of the benefits that the system brings to society.

The first chapter of this research studies the impact on the labor market of a public Social Security system that provides disability insurance benefits. This study searches for possible worker incentives to leave the labor force temporarily by comparing workers with the same health. Additionally, this study analyzes the extent to which workers with poor health continue to work because they lack social security coverage. I analyze the Brazilian disability insurance system, searching for possible incentives created by the system. The empirical analysis will be based on the system's rule that only formal-economy workers are covered, taking advantage of the considerable proportion of workers in informal jobs in the Brazilian labor market; however, as formalized workers may differ in other ways from workers in the informal sector, the approach will account for this heterogeneity. The results reveal that workers in the formal sector are more likely to take leave, even after controlling for health. This difference reveals the effects of such social protection systems on the labor market and, at the same time, reveals the inequality in opportunities faced by informal-sector workers. Moreover, as having a formal job does not affect workers' behavior when they have health problems, significant differences in the number of workers that take leave in the formal and informal sectors are not explained by differences in health status among these workers.

The second chapter of this research studies the effect of a series of changes to the Brazilian old-age pension on child labor and school enrollment. Child labor is still a considerable problem in Brazilian society. In 2001, 6.2% of children aged 5 to 14 years worked; however, this number jumps to 18.4% if we consider only children in rural areas. In addition, as the literature on child labor reveals, there are substantial consequences in terms of educational attainment for children prematurely involved in the labor market. This article analyzes the impact of the 1991 reform of the Brazilian rural pension system on child labor, literacy and school attendance. The 1991 social-security reform represents a good opportunity to investigate how income is allocated between household members because the reform generated an exogenous income shock: it decreased the minimum age for old-age pension eligibility and substantially increased the value of the minimum benefit. A significant proportion of Brazilian households, especially in rural areas, are composed of a mix of adults, children and elderly family members. Therefore, any changes in social-security benefits and eligibility rules may affect not only the beneficiaries but the other household members, as well. The empirical analysis uses a difference-in-difference estimator to identify the impact of the reform, where children affected by the reform (the treatment group) are compared with children not affected by the reform (the control group) before and after the reform. The results reveal an improvement in the educational attainments of children living with eligible males. Moreover, eligible females helped their grandchildren to leave the labor market in cases of child labor and facilitated their granddaughters' educations. The analysis of the impact on different socioeconomic levels shows that the impacts are concentrated in the lowest socioeconomic quintile. In contrast to what is found in the literature, our estimates suggest that men dedicate their additional income to their granddaughters' educations. One possible explanation is that men and women have different bargaining powers inside the family. There is evidence that the presence of female heads of household explain why eligible females appear to favor their granddaughter's education and to favor their grandsons in cases of child labor.

The second part of the research recognizes the importance of education to the future of the children's performance in the labor market; therefore, this study analyzes the impact of teacher quality on children's school performance. The reform of the public education system has played a major role in policy debates in Brazil over the last several years, especially after the universalization of standardized student-achievement evaluations. The disappointing performance of students on language and mathematics tests and the gap between students from public and private schools on most measures of academic achievement are source of concern to parents and policymakers, increasing the pressure to restructure the entire system. Nearly everyone involved in education recognizes the importance of teacher quality to student achievement; however, little is known about how teachers affect different kinds of students. This lack of knowledge is especially worrying when the public school system implements accountability programs, using student achievement in teacher assessments and putting pressure for achievement-related accountability on individual teachers and schools.

The measure of the impact of teacher quality on students is not straightforward, as we cannot simply compare groups of students from different teachers. Aside from teacher quality, the school performance of a group of students would depend on (i) the starting knowledge levels of students, (ii) their endowments (abilities and family backgrounds), and (iii) the teacher's working conditions (for example, the school's infrastructure). Therefore, the objective of this empirical analysis is to obtain estimates of differences in teacher contributions to student learning that account for the major sources of possible confounding from student heterogeneity and teacher assignment practices. The results reveal that low-achieving students exposed to better-quality teachers would expect to achieve 0.61 and 0.60 standard deviations higher in Portuguese and mathematics test-score performances. At the same time, high achieving students have Portuguese and mathematics scores increased by 0.57 and 0.73 standard deviations when exposed to better quality teachers; however, such impact represents a larger proportion of the average test score gains for high-achieving students. Moreover, if we analyze the impact of teachers on different students inside the same classroom, we also observe that students in the top of the test score distribution benefit more from better quality teachers.

Chapter 1

Impact of a Social Security System with Disability Insurance Coverage on the Labor Market

Priscila Pereira Deliberalli

1.1 Introduction

Disability insurance is an important segment of any modern Social Security system, providing workers with benefits when poor health prevents them from working. Rules differ between countries, and every system creates different incentive structures for its participants. Such benefits are a significant achievement for any society; however, they create disincentives to participate in the labor force. There is no consensus among economists as to the magnitude of such impacts. This paper will examine Brazil's disability insurance system, searching for system-created incentives to leave the labor force temporarily by comparing workers with the same health. Such questions become even more interesting because of the abrupt increase in the number of benefits in the Brazilian system that were claimed in the last decade, a phenomenon that raises several questions[1]. Better knowledge regarding the system's incentive structures is crucial for a better management of the program.

[1] There are some possible reasons, structural and non-structural, for such an increment in these benefits. They include (1) a government resolution which affected the rules on the screening process and the medical procedures to evaluate DI claims: INSS (Instituto Nacional de Seguridade Social) Resolution n.60/2001 in September of 2002 abolished the need to homologate medical exams and gave the power of the final decision to doctors, who now would not have to subject their decision-making process to anyone else. Even though Resolution n.60/2001 was revoked later that same month, the homologation of medical exams remained unnecessary. It remains to be seen if such an alteration in these operational rules represents an upgrade in the efficiency of the process, resulting in a faster provision of services, or if such resolution opened a hole in the legislation and allowed fraud and the granting of superfluous benefits; (2) the new Old-Age/Length of Contribution Benefit Formula (that created the "Fator Previdenciário"), which may have stimulated, after 1999, requirements of disability related benefits as an alternative source of income: Old-age benefits, now under new rules, would propitiate higher payments for those who retired later. The "Fator" rewarded (longer) years of contribution and resulted in a smaller replacement ratio relative to the previous replacement ratio of 100%. This possible explanation can be justified by the sharp difference in disability pension activity and by the change in the age-distribution of this kind of benefit after 1999. However, this is just speculation since there is no way to confirm that there was truly an intentional transfer from regular retirement benefits to disability ones. The only possible action to be taken to avoid the

Several researchers have sought to explain the interaction between social-insurance programs and labor-force participation. Most of the literature on disability-insurance (DI) disincentive effects focuses on the U.S. system, and the results are defined by the specific program. The different methodologies used in these studies significantly contributes to discussion of the problem; however, the usual methodology cannot be replicated to address the same issue in Brazil because the data are scarce. Moreover, the differences in program designs create different sets of incentives for the workers.

For that reason, this paper will address this issue in a slightly different way to address another important and interesting question. This study will examine the impact of a public Social Security system that provides disability-insurance benefits to the labor force. The results suggest the magnitude of the disincentive created by such benefits. The empirical strategy will be based on the system's coverage of only formal-sector workers and will take advantage of the considerate proportion of informal-economy workers in the Brazilian labor market. Therefore, this paper attempts to elucidate some of the possible disincentives created by the system by analyzing the differences between the behaviors of formal sector- and informal-sector workers, controlling for their health status. Moreover, this paper will analyze the extent to which the lack of coverage among informal-sector workers creates inequalities when workers in poor health are obliged to continue working.

As only formal-sector workers benefit from the system, a comparison of the temporary job absences of formal and informal-sector workers with the same health could signal that DI benefits encourage workers to temporarily leave the job market; however, formal and informal-sector workers cannot be directly compared to each other, as they have different characteristics. To account for this heterogeneity, we use propensity-score estimates to compare workers with the same probability of being in the formal sector based on demographic, labor-sector and occupation characteristics.

Moreover, we consider counterfactual estimates to explain the abrupt increase in new disability benefits after 2001. The aim is to determine the extent to which the

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granting of unnecessary disability pensions is to improve the medical investigation procedure, an action crucial to develop the system as a whole. Concerned with this problem, the Brazilian government attempted to introduce some marginal reforms on the bureaucratic concession process trying to increase efficiency of the system, since deeper reforms on social security are a political challenge to any government (Deliberalli (2004)).

changes in individuals' characteristics could explain the changes in the number of new DI benefits.

The paper is organized as follows. Section 2 briefly describes the Brazilian Social Security disability system and includes some statistics that help to illustrate the current situation and the motivation behind this study. Section 3 presents a literature review describing how the topic has been analyzed by other researchers. The next two sections describe the data and methodology employed to address the issue. The sixth section presents results suggesting that formal-sector workers, covered by the system, tend to be "on leave" (taking advantage of disability insurance) more frequently than informal-sector workers. The last section summarizes the conclusions.

1.2 Disability Insurance Benefits: Rules of the System

The disability program in the Brazilian pension system includes three main classes of benefits: sickness benefits, disability pensions and occupational-injury benefits, which include a sickness benefit, a disability pension and an accident-compensation benefit. Moreover, the law guarantees rehabilitation for totally or partially disabled beneficiaries and rehabilitation for handicapped workers[2].

Workers become eligible for the sickness benefit if any ailment results in the inability to work. Payment starts after 16 days of absence or after the date the benefit was claimed if there are more than 30 days difference between this date and the beginning of the period of absence. The first 15 days of absence are paid by the employee. The vesting period is 12 months, and the benefit corresponds to 91% of the "salário-de-benefício"[3].

[2] The law guarantees rehabilitation for totally or partially incapable beneficiaries and habilitation to handicapped workers. This includes the supply of prosthesis and other instruments that could attenuate the loss of capacity or mobility. In order to relocate and guarantee the participation of disabled workers in the labor market. Moreover, the government requires that firms with more than 100 employees fill between 2% and 5%, depending on the number of employees, of their labor force with disabled and rehabilitated workers. However, it is necessary to investigate to what extent this rule is obeyed by the firms and what the penalties are for non-compliance.

[3] "Salário-de-benefício" is the base for all of the benefits of the social security system in Brazil. For disability benefits, "salário-de-benefício" is the average of the highest 80% of wages/remuneration since July 1994. The government is trying to change this formula for some disability related benefits, as will be discussed later. However, nothing has been approved by congress yet. It is worth mentioning that all of the

No maximum period of payment for this benefit is specified by law, although it is considered temporary.

Workers become eligible for the disability pension if they are considered incapable of activities to guarantee financial viability and are unsuitable for rehabilitation. As in the sickness benefit, employees pay the first 15 days of absence. The payment starts after the end of the sickness benefit. If there was no previous sickness benefit, the payment starts after 16 days of absence or after the date the benefit was claimed if there are more than 30 days' difference between this date and the beginning of the period of absence. The vesting period is 12 months, and the benefit corresponds to 100% of the "salário-de-benefício". Moreover, the benefit value is supplemented by 25% if the beneficiary requires constant personal care.

The system of occupational-injury benefits includes a sickness benefit, a disability pension and an accident-compensation benefit. For the first two kinds of benefit, the payments are calculated the same way as described before. There is, however, no vesting period for work-related benefits. Workers become eligible for the accident-compensation benefit if work-related accidents result in diminished work capacity. This benefit is independent of any other remuneration and starts after the end of the sickness benefit payments. The benefit corresponds to 50% of the "salário-de-benefício" and cannot be paid when the worker is receiving any kind of retirement/disability pension (but it is added to the wage when retirement is calculated).

This paper focuses on sickness benefits (occupationally related or otherwise). In the standard terminology, these are disability-insurance (DI) benefits.

As informal workers do not have any legal rights, their ability to take leave would depend on the kind of job they do or on the generosity of the employer. For example, a self-employed informal worker may temporarily stop working, but only at the expense of his own "wage" or revenue. On the other hand, a maid that works informally but with a relatively generous family[4] may take leave if she gets sick and still be paid by her employers; however, neither has any legal rights or government protection.

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benefits are inflation-indexed and updated once a year using the National Consumer Price Index (INPC). Furthermore, there is a bottom limit for the benefits to equal at least the minimum wage.

[4] Not generous enough to hire her as a formal worker.

Two kinds of social protection networks that are available in Brazil to those who never contributed to Social Security, but neither relates to unemployment insurance or disability insurance. The first network is a conditional cash-transfer program (Bolsa Familia) that transfers resources to families with children. The amount transferred depends on the number of children and their ages, with a maximum total benefit value approaching ½ minimum wage. To be eligible, family per-capita income must be less than ¼ minimum wage. Informal workers who can rely on that benefit would have more advantage if they get sick and decide to take leave compared to those workers that do not have access to this benefit. At the same time, that program is available to any lower-income family with children, meaning that formal-sector workers also have access; however, considering the average income of workers in the formal and informal sector, it is unlikely that most workers eligible for "Bolsa Familia" work in the formal sector. Therefore, this benefit would likely increase the probability that informal workers will take leave, lessening the impacts we find in this paper.

The second social protection network available to informal workers is called LOAS (Social Assistance Benefit). Eligible workers (i) are 65 years or older, do not receive any other social security benefit, and have a per-capita income less than ¼ of minimum wage; or (ii) are permanently disabled, with a per-capita income lower than ¼ of minimum wage. As my study considers only employed workers (on leave), workers that are already permanently disabled and out of the labor force are excluded; therefore, the LOAS would not influence the probability of their taking leave.

1.3 Literature Review

This section summarizes some studies on the disincentivizing effects of disability insurance (DI) in the U.S., describing the characteristics of this system. The main differences between the U.S. and the Brazilian system and the data availability will be emphasized to justify the methodology applied in this paper.

Originally, the Social Security disability-insurance program (SSDI) in the U.S. was designed for workers suffering from impairment of continued and indefinite duration; however, in 1965, "the definition of disability was liberalized to allow those without permanent disabilities to qualify"[5]. Eligibility is conditioned on previous sufficient employment in jobs covered by Social Security. Differences between the Brazilian and the U.S. system do not allow direct comparison of the results; however, the literature on the U.S. system suggests that some degree of disincentive is created by DI programs. This paper aims to analyze the extent to which the same disincentivization happens in Brazil.

The major problem in identifying the disincentivizing effects of DI programs is the absence of information about the potential labor supply of beneficiaries. The main methodological problem faced by researchers when addressing these impacts on labor-force participation (LFP) is the endogeneity of the DI benefits. Participation in DI programs is based on a combination of an individual's decision to apply for the program and the individual's eligibility for the program. Therefore, DI benefits cannot be treated as exogenous variable in a labor-force participation equation.

To manage this endogeneity problem, several studies have tried to model LFP as a function of the potential benefit levels by wage, known as the replacement rate; however, this method presents certain problems, as well. Depending on the mechanism of benefit calculation, the replacement ratio may differ among workers with different wage levels and work histories. Thus, as benefits depend on past wages, they depend on past work decisions, as well, and the replacement rate cannot also be considered an exogenous variable. Moreover, the replacement rate combines wage and benefit levels, confounding their impacts on LFP.

A series of studies has attempted to evaluate the work capability of DI claimants and measure the degree of disincentive attributed to DI programs in the U.S. Parson (1980) modeled labor-force participation as a function of replacement rates and demographic and health characteristics. This researcher compared the participation rates in labor forces with high and low replacement rates. The difference in participation rates between these two groups is taken to be an estimate of the DI disincentive; however, as mentioned before, this strategy does not consider the endogeneity of replacement ratios. As replacement ratios are a decreasing function of past earnings and incentive structure, it

[5] Bound (1989).

is not possible to determine whether it was generous replacement rates or low earnings that induced individuals to leave the labor force.

Bound (1989) suggested that there is a causal connection between the availability and generosity of DI benefits and the increasing proportion of older men leaving the labor force to qualify for the benefits; the proportion of older men out of the labor force increased as DI benefits grew rapidly due to the higher availability and generosity of the system. This estimation strategy considered rejected applicants as a control group for the beneficiaries. Bound assumed that rejected applicants are healthier and more capable of work than those who were accepted; therefore, their labor-force participation should provide an upper bound for what could be expected of DI beneficiaries. Bound found that fewer than 50% of rejected male applicants work and that less than half of those on DI would work were they not receiving benefits.

As Autor and Duggan (2006) observed, this methodology may be biased towards underestimating the labor disincentive of the disability insurance system for two reasons: “some rejected applicants may remain out of labor force because they are reapplying for DI while other rejected applicants may be unable to find re-employment because their skills and opportunities deteriorated during the application process”. Another limitation is that low-skilled, but not disabled, workers who would not be working but who filled out applications distort this comparison between rejected and non-rejected claimants.

Chen and Van der Klaauw (2006) evaluated the work-disincentive effects of DI programs in the 1990s. These researchers replicated the Bound upper bound for the work-disincentive effect of the current program and subsequently adopted a Regression-Discontinuity approach to provide a point estimate of the impact of the DI program on “marginal applicants who are not immediately awarded or denied benefits on the basis on their specific medical impairment and whose eligibility needs to be determined by considering vocational factors”. More specifically, exploiting the fact that for approximately 40% of applicants, disability determination was not resolved based on medical grounds, these researchers analyzed the particularities of the determination process that access the residual capacity of a worker based on the grid, causing a discontinuity on the probability of being awarded depending on age[6]. As the individuals are of similar age when they are just below or above the cutoff age, those just below the cutoff age are comparable to the individuals just above it in all characteristics. Consequently, these individuals are expected to have similar labor-supply responses when receiving DI benefits. The authors held that the average LFP of individuals just below the cutoff age could be a credible estimate of what the LFP of those just above the cutoff would have been if they had not been awarded the DI benefit. Their estimates imply that "the LFP rate of DI beneficiaries would have been at most 20 percentage points higher had they not received benefits", suggesting a smaller disincentive than the one estimated by Bound[7].

The U.S. and the Brazilian systems present several significant differences, resulting in diverse disincentive effects. The rules in the U.S. and the Brazilian Social Security systems differ, and the degrees of disincentive brought to the labor markets are different as well.

The Brazilian screening process does not include as many steps to identify qualified applicants. The decision is based on health status and the capacity to carry out the worker's "current" job. The fact that Brazilian rules require workers to be currently enrolled in jobs covered by Social Security represents a significant difference between

[6] The U.S. disability determination process is based on medical and vocational factors such age, education and past employment, all used to determine an individual's ability to work. After going through nonmedical criteria (to be eligible, individuals must be under 65—and now 67 for those born in 1960 or later—, must have worked for at least 5 of the last 10 years and cannot be "engaged in a substation gainful activity" (no more than $860 monthly earnings in 2006), severity assessment evaluates if an applicant has an impairment that meets a specific codified clinical criterion relating to both the nature and the severity of impairment, which defines benefit award. If a benefit is not awarded, the next step is to evaluate the applicant's ability to work, based on his/her characteristics including health condition. If offices conclude that the applicant cannot work, then a benefit is awarded. Both the individual's ability to perform the job he had before the onset of the disability and his residual functional capacity to work are evaluated. If he is considered able to perform his past job, the benefit is denied. If he is considered unable to perform his past job, than he moves onto the next stage, where the residual functional capacity determined before is combined with vocational characteristics such as age, education and work experience to determine if he can carry out alternative types of work in the economy, other than the one he had held. A grid is provided to help guide the decision. The grid regulations relate certain workers' characteristics such as age, education and past work experience to the individuals' residual capacity to perform work-related physical and mental activities. Individuals are characterized by different age groups (under 45, 45 to 49, 50 to 54, and 55 and over) and by different residual functional capacities (sedentary, light or medium) previously determined and based on medical condition, experience and skill level. If an applicant's request is denied, it is possible to appeal.

[6] Several authors have discussed some potential reasons for the different results. For more detail, see reference.

[7] Several authors have discussed some potential reasons for the different results. For more detail, see reference.

the two systems. As a result, an evaluation of a worker's residual capacity to work would suggest that an applicant leave a job he/she is unable to perform and find another suited to his/her potential.

Two potential consequences of the design differences should be considered. First, because U.S. eligibility requirements are conditioned on the applicant's not being engaged in any activity that is both "substantial and gainful", the system could create higher incentives for non-labor participation; however, as the final step of the U.S. screening process is an assessment of the residual functional capacity, i.e., it verifies whether the applicant can carry out any type of work in the economy. For this reason, the U.S. system may grant benefits to truly disabled workers more frequently than does the Brazilian system.

The strategies used by the papers just described could not be applied to analyze the disincentive effects of disability insurance in Brazil, due to insufficient data. Considering the availability of data in Brazil, this paper will address this issue in a slightly different way, but it will answer another important and interesting question. This paper will examine the impact of a public Social Security system that provides disability-insurance benefits on the probability of being "on leave". The results suggest the magnitude of the disincentivizing effects of such benefits. The empirical strategy will be based on the system's coverage of formal-sector workers alone. The analysis will take advantage of the considerable proportion of the Brazilian labor market that is informally employed.

1.4 Data

This paper uses data from the Brazilian Household Survey (Pesquisa Nacional por Amostras de Domicílios – PNAD) conducted by the Brazilian Census Bureau (Instituto Brasileiro de Geografia e Estatística – IBGE), which is an annual household survey with a sample size equal to 1/500 of the Brazilian population. We first use the 2003 survey, which includes a supplement about health. One of the greatest obstacles to be surpassed in addressing the problem of the DI disincentive as the literature does would be to identify workers receiving DI benefits, as no specific question identifies them on the

PNAD. Other Brazilian household surveys do contain such identification but do not contain sufficient information about labor-force participation.

As mentioned previously, Social Security covers only formal-sector workers. In that sense, informal workers would provide a control group for formal-sector workers. Controlling for demographics, labor sectors, occupations and health, formal workers would have a smaller labor-force participation than informal workers if the DI benefit induces a degree of disincentive to return to the labor force or an incentive to leave it momentarily. For that reason, the comparison between formal and informal workers would bring some light to the discussion about the disincentives caused by DI benefits.

The dependent variable comes from answering the following question: "Were you temporarily away from a paid job on the reference week?"[8]. The "treatment group" (formal-sector workers) includes workers who contribute to Social Security and are therefore eligible to the system. The health-condition dummy variables are based on a self-reported health-status variable.

Using formal-sector workers rather than the actual beneficiaries as the "treatment group" (the "intent-to-treat" approach) helps to manage the endogeneity problem in studying the impact of DI benefits on the labor force. Nevertheless, as mentioned before, formal and informal workers cannot be directly compared to each other, as they have different characteristics; thus, this variable (dummy for a formal-sector worker) also cannot be considered exogenous, rendering the estimates inconsistent. The chosen methodology will mitigate this problem as described below.

The sample includes employed private-sector workers in non-rural employment. Rural workers were excluded because most of them have no formal job positions. Furthermore, as rural workers tend to have specific characteristics like low education levels, using these individuals in the sample could bias the results. Public sector workers were also excluded, as they work under a specific Social Security regime that differs from the private-sector regime.

[8] Only people who previously declared themselves as employed had the opportunity to answer this question.

Table 1 presents some descriptive statistics of the sample of formal- and informal-[9] sector workers. As would be expected, formal- and informal-sector workers differ in almost all demographic and occupational characteristics. Workers enrolled in formal jobs are mainly married white men, are more educated than informal workers, live in the South and Southeast, and perform jobs in the manufacturing, health and education sectors.

Workers who declared themselves to be in excellent health belonged mostly to the formal sector. On the other hand, workers who declared themselves to be in normal, poor or very poor health worked mainly in the informal sector. Interestingly, approximately 6.6% of informal workers declared that they did not undertake some activity on the week before the survey for health reasons, while among formal-sector workers, only 5.1% reported such limitations. In contrast, only 0.97% of informal workers (versus 2.5% of formal workers) were "on leave" in the reference week.

We used the 1998 PNAD[10] to estimate counterfactual probabilities. The aim is to characterize the extent to which the changes in individuals' characteristics from 1998 to 2003 could explain the increase in the number of new disability-insurance benefits.

Moreover, the estimation of difference-in-difference estimates between the 1998 and 2003 data will show that the identification strategy (using formal-sector workers as the "treatment group" and informal-sector workers as the "control group") can capture the considerable increase in the number of disabilities benefits between these two periods.

1.5 Empirical Strategy and Methodology

Differences in the labor market, program design and data availability require an alternative methodology to examine the disincentivizing effects of DI programs. This requirement will compromise any result comparisons with the previous literature for the U.S. system; however, it will contribute to the discussion of disincentive effects of DI benefits.

[9] We defined formal sector workers as those who contribute to Social Security (called INSS in Brazil).
[10] The 1998 PNAD includes a health supplement as well.

The same endogeneity issues inherent in the analysis of DI disincentive effects complicate this analysis; unobserved attributes that make job formality more likely may be correlated with LFP (in this paper, a binary variable that measures temporary labor-force absence or the probability of being "on leave"). Therefore, a single-equation estimate of the effect of a formal job on LFP (equation (1)) would be biased. The likelihood of being a formal-sector worker ($t_i = 1$) is probably correlated with variables (Xs) that influence the LFP or the probability of being "on leave".

$$LFP_i = \alpha + \beta X_i + \gamma t_i + \varepsilon_i \qquad (1)$$

To mitigate the potential bias due to unobserved heterogeneity (between treatment and control groups) and endogeneity problems, Rosembaum and Rubin (1983) developed the propensity-score-matching estimators. In this method, each treatment unit (covered or formal-sector workers) is matched with non-treatment units (non-covered or informal-sector workers) under the assumption of conditional independence, i.e., $LFPi \perp t_i / X_i$ and common support, i.e., $0 < Prob(t_i = 1 / X_i) < 1$, (Mocan and Tekin, 2002). The propensity-score method is used to control for the differences between the treatment and control groups. Therefore, we guarantee that comparisons are made between homogeneous workers; after controlling for the observed characteristics (Xs), assignment to treatment and control groups would be random.

Each formal-sector worker (treated unit) can be matched with an informal-sector worker (control unit), and the average treatment effect is calculated as the mean within-match difference in the outcome variable (probability of being "on leave") between treated and non-treated observations.

The idea behind this propensity-score method is that conditional independence and common-support assumptions imply that "whereas one conditional on X in traditional matching estimators, in propensity score matching estimators one conditions on the propensity score because observations with the same propensity score have the same distribution of covariates, X" (Mocan and Tekin, 2002). Therefore:

$$LFP_i \perp t_i / p(X_i) \text{ and } 0 < Prob(t_i = 1 / p(X_i)) < 1$$

The first step in the method is the estimation of a probit regression to estimate the propensity score. "Rosembaum and Rubin (1983) define a propensity score as a function of the vector X, such that $X_i \perp t_i \,/\, p(X_i)$, i.e., conditional on the propensity score, the covariates are independent of assignment to treatment" (Mocan and Tekin, 2002). Therefore, the distribution of the variables in vector X should be the same across treated and non-treated individuals for observations with the same propensity score (the Balance Property). The idea behind this method considers that the bias is reduced when comparing treated and non-treated individuals that are as alike as possible. The extent to which the bias is eliminated depends on the quality of the control variables used when estimating the propensity score.

The second step involves the estimation of the average treatment effect on the treated (ATT). Following (Mocan and Tekin, 2002), the ATT estimation can be specified as follows:

$$\begin{aligned} E(\Delta_i / t_i = 1) &= E\{(LFP_i = 0, LFP_i = 1) / t_i = 1\} \\ &= E\{E\{(LFP_i = 0, LFP_i = 1) / t_i = 1, p(X_i)\}\} \\ &= E\{E\{LFP_i = 1 / t_i = 1, p(X_i)\}\} - E\{E\{LFP_i = 0 / t_i = 1, p(X_i)\}\} \end{aligned}$$

The empirical strategy in this paper estimates the probability of $LFP_i = 1$ (in this context, probability of worker being "on leave") among workers with a similar propensity score (in this paper, the probability of working in a formal job). Five groups were defined based on the estimated probability of being a formal-sector worker. Accordingly, for workers in each of these five groups, the probability of being "on leave" was estimated as follows:

$$\text{Prob (on leave)}_{ij} = \alpha_j + \beta Z_{ij} + \gamma t_{ij} + \varepsilon_{ij} \quad , \qquad (2)$$

where vector Z contains health-condition variables. Equation (2) estimates the probability of a worker being "on leave" for workers with the same propensity (j = 1, …, 5), the impact of having a formal job and the impact of coverage by the DI program. Each of the j equations estimated considers workers with a similar propensity. To determine the consistency of the estimates, we estimated the probability of being “on leave” for j = 1, …, 10, as well.

Next, to confirm the findings above, the Average Treatment Effect on the Treated (ATT) will be measured using Nearest-Neighbor Matching (NNM) estimators; as p(X) is a continuous variable, there are no two individuals with the same p(X). The NNM estimator will take each treated unit and search for the nearest control unit, i.e., the control unit with the closest p(X). Once treated and control units are matched, the difference between the treated and control outcomes is computed. The ATT is the average of all these differences (Becker and Ichino (2002)).

The results will show that the estimates may still be biased, as the Balance Property is not totally satisfied, even though treatment and control groups are more similar when considering individuals with the same propensity score.

The next step is to run the counterfactual decomposition method developed by Oaxaca (1973) and Blinder (1973), which is employed to analyze the mean outcome differences between workers in 1998 and 2003. The idea is to observe the extent to which the changes in individuals’ attributes from 1998 to 2003 could explain the changes in the number of new disability-insurance benefits. Again, our dependent variable is a dummy that captures whether a worker is “on leave”, as we do not have information concerning who receives the benefit.

Following Jann (2008), consider our outcome variable Y (dummy equals one if worker is on leave). The question is how much of the difference between $E(Y_{1998})$ and $E(Y_{2003})$ is explained by differences in individual characteristics between these two groups of workers. Therefore, the method divides the differences in the probability of being “on leave” between workers in 1998 and 2003 in into group characteristics and a residual that is not accounted for by such characteristics. Suppose we estimate the model below:

$$Y_g = X_g'\beta_g + e_g \qquad \text{where } g = 1998, 2003 \qquad E(e_g) = 0$$

The mean outcome difference can be expressed as the difference between the $E(Y_g)$ for each group:

$$R = E(Y_{1998}) - E(Y_{2003}) = E(X_{1998})' \beta_{1998} - E(X_{2003})' \beta_{2003} \qquad \text{as } E(e_g) = 0$$

$$R = [E(X_{1998}) - E(X_{2003})]' \beta_{2003} + E(X_{2003})'(\beta_{1998} - \beta_{2003}) + [E(X_{1998}) - E(X_{2003})]' (\beta_{1998} - \beta_{2003})$$

Therefore, the outcome difference can be divided into three parts:

$$R = E + C + I,$$

where

$E = [E(X_{1998}) - E(X_{2003})]' \beta_{2003}$ is the "endowment effect" and shows the part of the differential explained by group differences in the independent variables

$C = E(X_{2003})'(\beta_{1998} - \beta_{2003})$ is the part of the differential explained by coefficient differences among the two groups

$I = [E(X_{1998}) - E(X_{2003})]' (\beta_{1998} - \beta_{2003})$ "is an interaction term accounting for the fact that differences in endowment and coefficients exist simultaneously between the two groups" (Jann, 2008)

The model estimated is as follows:

$$E(\text{on leave}) = \alpha + \beta X + \gamma t + \varepsilon,$$

where t represents the dummy variable for workers in the formal sector, and X includes socioeconomics characteristics and health status characteristics.

1.6 Results

As there are no data for which we can identify the actual benefit recipients, this paper will employ an intent-to-treat approach, where the actual treatment will be replaced by eligibility for participation in the system. Another positive aspect of such an approach is that it avoids the selectivity problem. Therefore, the first step is to estimate the probability of receiving treatment, i.e., to be eligible to receive the benefit, as is the case for all workers who contribute to Social Security (called INSS in Brazil). We will call these eligible individuals “formal workers”.

To obtain the values of the propensity to work in the formal sector, the first step was to estimate probits for the whole sample and separately for men and women as a function of their other demographic and labor-market characteristics. Table 2 shows that all these variables turned out to be significant to the determination of the probability of being a formal worker[11]. As expected, workers with a higher likelihood of being formal-sector workers are more likely to be educated, white, living in metropolitan areas and employed in the manufacturing, health and education sectors. Based on these results, workers were classified into five groups according to the estimated probabilities of working in a formal-sector job (or their propensity scores). To check the consistency of the estimates, workers were grouped into ten different blocks, as well, based on the same probabilities.

Graphs 1, 1a and 1b show that once we separate workers based on the estimated probability of being in the formal sector, the probability density function of informal workers approaches the density function of formal workers, especially for workers in the lower and upper tails of the distribution.

The next step in assessing the effect of Social Security on the LFP is to estimate the impact of a formal-sector job in the probability of being “on leave” among workers with the same likelihood of being formal-sector workers. The Balance Property requires that the distribution of the exogenous variables be the same across formal (treated) and informal (non-treated) sector workers for individuals with the same propensity score. Table 4 reveals that even though treatment and control groups (formal and informal workers) are different with respect to demographic and labor characteristics, once we consider individuals with the same propensity score, these differences decrease considerably.

[11] This excludes variables like “other occupation” and “public administration sector” as few individuals present such characteristics.

Table 5 shows the estimated probability of being "on leave", controlling for workers' health. Tables 5a and 5b display a similar estimation for women and men separately. They reveal the impact created by the disability system; among workers with the same likelihood of being in the formal sector, those in formal jobs have a higher probability of being "on leave". Considering the entire sample, Table 5 shows that workers eligible for the system have a probability of being temporarily absent from their jobs 0.47 points higher than that of workers who are not eligible for the system, even after controlling for health status. As discussed before, however, workers from formal and informal sectors have different demographic characteristics; therefore, these differences could explain such result; however, after separating workers based on the probability of being in the formal sector, we find similar results. For the five different groups defined by the probability of being a formal worker, having a formal job increases the probability of being "on leave" by more than 0.4 points (0.35 to 0.51, depending on the likelihood of being in the formal sector). If we increase the similarity of workers inside each group based on the probability of working as a formal worker and increase the number of groups from five to ten, the results are maintained[12].

It is worth mentioning that workers in poor health have a much smaller probability of being "on leave" if they have a low likelihood of being in the formal sector. Better health, as expected, seems to decrease the probability of being "on leave", especially for men; however, as the health variable is a self-reported health, it seems that there is no difference between individuals that declared themselves as being in "really good health" and "good health".

Tables 5a and 5b include estimates for females and males separately; again, we find that workers eligible for the benefit have higher a probability of being on leave. The impact for eligible females with the lowest probability of being in the formal sector is almost twice as high as the impact for the other groups of females, revealing that uneducated females with low-skilled jobs tend to take fuller advantage of such benefits than highly educated women in managerial positions. Conversely, male workers in the same group (lower probability of being in the formal sector) do not have a higher

[12] We do not find significant results among workers in the top of the distribution of the probability of being in the formal sector in the case (Prob(formal) > 0.9). Results upon request.

probability of being on leave than do men in different groups. Applying nearest-neighbor matching estimators, we find smaller but still significant results (Table 6).

The results suggest that it is necessary to increase the formality of the Brazilian labor market such that individuals whose health would prevent them from working do not continue to work. On the other hand, although increasing the proportion of formal jobs is desirable, the considerable increase in the granting of new DI benefits after 2001[13] suggests that the granting rules might be creating unwanted incentives for people to temporarily leave the labor force.

To test the quality of the dependent variable that indicates whether workers are temporarily absent from their jobs, we run the same estimates using a different dependent variable[14] that reveals whether a worker did not undertake any regular activity due to health problems. As this question does not focus on job-related activities (and therefore would not necessarily involve any benefit payment in case of an affirmative answer), we should not expect any difference between formal- and informal-sector workers after controlling for health characteristics. In fact, we observe no significant impact of having a formal sector job on the probability of quitting any activity for health reasons. Moreover, if we consider a dependent variable that consider workers “on leave” and who avoided any regular activity due to health problems, we find stronger effects (coefficients are higher). We expect that the probability of taking leave for health reasons should be significantly different between formal and informal workers if informal workers feel unable to stop working due to the lack of benefits coverage; see Appendix for results. Therefore, as we do not find that having a formal job affects workers’ behavior when they have health problems, the significant differences in the number of workers that take leave in the formal and informal sector are not explained by differences in health status among these workers.

It is worth remembering that there was a significant increase in the number of new disability benefits after 2001. The identification strategy employed in the paper is able to capture this movement, what we can see in Table 7, which shows the difference in difference estimate of the change in the impact of being a formal-sector worker in the

[13] As mentioned before, it is not clear what caused such an abrupt increase in the number of benefits. However, some changes in the granting rules seem to have contributed to such fact.
[14] This variable comes from the Health Supplement.

probability of being “on leave”. Calling 2003 observations “Post”, we observe that after controlling for the time trend and treatment (formal workers), the variable “Post x Treatment” (difference in difference estimate) is significant in explaining the LFP. Although it is not possible to point to the specific reason for such an increase in the number of disability benefits (as we briefly discussed before), the identification strategy (intend-to-treat approach) seems to illustrate this point.

Table 8 presents the counterfactual probability estimates. The first part of the table reveals that the probability of being “on leave” is 0.64 percentage points smaller in 1998. The first line of the second part of table reflects the mean decrease in the probability of being “on leave” if 2003 workers had 1998 workers’ characteristics. Differences in endownment account for approximately 13% of the differential (-0.08 of -0.64). The second line reflects the changes in the probability of being “on leave” if we apply 1998 worker coefficients to the 2003 worker characteristics. Approximately 86% of the probability difference among 1998 and 2003 workers is explained by such coefficient differences (-0.55 of -0.64). The third part measures the impact of differences in endownment and coefficients (the interaction term), but such effect is not significant. Therefore, individual characteristics changes are not able to explain all of the considerable increases in the granting of new DI benefits after 2001.

1.7 Conclusions

This study took advantage of the high proportion of informal-sector workers, uncovered by Social Security, to analyze the impact of such system on the labor force participation of Brazilian workers. After controlling for the demographic and labor market characteristics, informal-sector workers would be a control group for formal-sector workers covered by Social Security. The identification strategy employed in the paper is able to capture the strong increase in the number of new DI benefits observed in the Brazilian economy after 2001.

To manage the endogeneity of the variable that separates formal and informal-sector workers in a single labor-force-participation (LFP) equation estimation, the probability of being “on leave” was estimated separately for workers with the same propensity to work in a formal-sector job. Although the Balanced Property cannot be totally satisfied, we can considerably reduce the heterogeneity between the treatment and control groups by estimating the treatment effect for individuals with the same propensity score.

The results reveal that workers in the formal sector have a higher probability of being “on leave”, even after controlling for health, which suggests the degree of disincentive created by such social protection system. At the same time, workers with poor health have a higher probability of working if they in the informal sector. Moreover, as we do not find that having a formal job affects workers’ behavior when they have health problems, the significant differences in the number of workers that take leave in the formal and informal sector are not explained by differences in health status among these workers.

Providing workers with benefits when sickness prevents them from working is an important role of any modern Social Security system. However, even though such benefits are an important achievement for any society, some benefit structures may create disincentives to participate in the labor force. This paper suggests either that workers from the formal sector may take advantage of the system to be “on leave” from their jobs, even when their health statuses do not require that they do so; the results also suggest that it is necessary to increase the formality of the Brazilian labor market such that individuals whose health is too poor to work are not forced to continue working; however, as some small granting-rule modifications seem to have caused an abrupt increase in the number of new DI benefits, we believe that the design of the system can be improved to avoid creating undesired incentives.

Chapter 2

Old-Age Benefits and Income Bargaining Effects on Child Labor and Education in Brazil

Priscila Pereira Deliberalli

Vladimir Ponczek

2.1 Introduction

This paper studies the effect of a series of changes to the Brazilian old-age pension on child labor and school enrollment. Child labor is still a considerable problem in Brazilian society. In 2001, 6.2% of children aged 5 to 14 years worked; however, this number increases to 18.4% if we consider only children in rural areas[15]. In addition, as the literature on child labor reveals, there are substantial consequences in terms of educational attainment for children prematurely involved in the labor market[16].

This article will analyze the impact of the 1991 reform of the Brazilian rural pension system on child labor, literacy and school attendance. The 1991 social-security reform decreased the minimum age for old-age pension eligibility and substantially increased the value of the minimum benefit. Before the reform, there was a flat old-age benefit (equal to half the minimum wage) for rural areas, and only one member of the household was eligible (usually the head). The minimum eligibility age was 65 years for men and 60 years for women. After the reform, more than one family member could be eligible for benefits, and the minimum benefit value was set equal to minimum wage. The minimum eligibility age for old-age benefits was reduced to 60 years for men and 55 years for women.

A significant proportion of Brazilian households, especially in rural areas, are formed of a mix of adults, children and elderly members. Therefore, any changes in social-security benefits and eligibility rules may affect not only the beneficiaries but the

[15] Brazil National Labor Survey (SIMPOC) (2001) in *Brazil: Child Labor Data Country Brief* (2008) ILO

[16] There are different views regarding the impact of child labor on education. The literature review section will discuss this causal relationship in detail.

other household members, as well. Hence, the 1991 reform represents a good opportunity to investigate how income is allocated among household members, as the reform generated an exogenous income shock. If we consider that the intra-household allocation model is not uniform and that each agent may behave differently, the changes in the eligibility rules and benefit amounts would have an impact different from any other ordinary income shock if the preferences of the elderly are not the same as those of the other adults in the household. The empirical strategy considers a difference-in-difference estimator to identify the impact of the reform, where children affected by the reform (the treatment group) are compared with children not affected by the reform (the control group) before and after the reform; however, selectivity bias could occur because the decision to apply for the benefit could be endogenous. To manage these issues, instead of creating the actual treatment group, an *intent-to-treat* group that considers all of the eligible elderly will be created. Additionally, families with elderly members may differ from families with no elderly members. Therefore, the treatment group is composed of members of households with an eligible elderly member (under the new and old rules of the system) and the control group is composed of members of households with elderly members who are not old enough to be eligible (men between 55 and 60 years, and women between 50 and 55 years). We believe that this strategy represents an important improvement over Carvalho (2000), as it can be used to build similar control and treatment groups, making our findings more robust and accounting for the heterogeneity between children living with an elderly member and children not living with one. The heterogeneity between the treatment group and such a control group could jeopardize the consistency of the estimation if it is not properly addressed.

Aside from understanding the positive externalities that old-age benefits bring to society, the objective of this paper is to analyze the intuitive idea that child labor emerges from the poorest households; therefore, this paper studies the impact of changes to the Brazilian old-age pension on child labor and school attendance in families from different income quantiles and socioeconomic levels. The results would still contribute to knowledge of intra-household allocation models, as the findings would show whether an income shock targeting grandparents would affect resource allocation to children. Clear theoretical and empirical comprehension is crucial when designing policies to mitigate the problem, as well-intentioned policies may exacerbate child poverty if they are not correctly designed.

The results reveal improvement in the educational attainments of children living with eligible males. Moreover, eligible females helped their grandchildren to leave the labor market in cases of child labor and supported their granddaughters' education. The analysis of the socioeconomic index shows that the impacts are concentrated in the lowest socioeconomic quintile. In opposition to the literature, our estimates suggest that men dedicate their additional income to the education of their granddaughters. One possible explanation is that men and women have different bargaining powers inside the family. The presence of female heads of household explains why eligible females seem to favor their granddaughter's education and to favor their grandsons in cases of child labor.

2.2 The Social Security Reform and Literature on the Impact of Income on Child Labor

In 1988, the new federal constitution was approved in Brazil, instituting several changes to the entire social security system, such as equalization of rural and urban benefits; extension of old-age benefits to all family members; a mandate that no benefit should be smaller than the minimum wage; a reduction in the minimum age for old-age eligibility; and length-of-service eligibility for rural workers; however, as the new constitution stipulated, Congress should pass ordinary laws to implement these changes, as was performed on July 24, 1991[17].

Before the reform, there was a flat old-age benefit (equal to half the minimum wage) for rural areas and only one member of the household was eligible (usually the head). The minimum age of eligibility was 65 years for men and 60 years for women. After the reform, more than one family member could be eligible for benefits and the minimum benefit value was set equal to the minimum wage. The minimum eligibility age for old-age benefits was reduced to 60 years for men and 55 years for women. Besides the old-age benefit, rural workers could apply to receive length-of-service benefits for

[17] Laws n. 8212 and n. 8213, available at
http://www81.dataprev.gov.br/sislex/paginas/42/1991/8212.htm
http://www3.dataprev.gov.br/sislex/paginas/42/1991/8213.htm

which workers who worked for at least 30 years (for men) or 25 years (for women) and contributed to Social Security were eligible. The value of this benefit was based on the earnings that the worker contributed to the system; however, at least until the end of the 1990s, most rural workers failed to keep records documenting their previous earnings and therefore could mostly apply only for the old-age benefit. According to the Social Security Administration, the average rural benefit in 1997 was R$121, while the monthly minimum wage was R$120; moreover, less than 0.1% of the rural system pensioners were under the length-of-service regime (Ponczek, 2011). Therefore, it is not necessary to be concerned with any possible endogeneity caused by different benefit values.

The increase in the benefit for eligible beneficiaries under the pre-reform rule (the old rules) was automatic, i.e., as soon as Congress approved the reform, the value of the benefit doubled. Conversely, workers who became eligible after the reform (under the new rules) had to go through a registration process that took several months, due to administrative red tape. Therefore, the income shock for this group was not automatic. For that reason, we use data from 1992, 1993 and 1995 for the post-reform period to allow enough time for completion of this registration process. Moreover, as workers must apply for the benefit, selectivity bias may emerge; the characteristics that drive a worker's decision to apply might be correlated with the outcome of interest. The approach used (which will be described) deals with this concern.

As the value of income shock differs for workers eligible under the old rules and workers eligible under the new rules, we create four different treatment groups. We discuss this strategy in detail later.

The 1991 reform generated an exogenous income shock and represents a good opportunity to investigate how income is allocated between household members and how such an income shock might affect child labor and educational attainment.

The number of children in the labor market has decreased in recent years, but it is still significantly large. In 1992, 22% of children between 5 and 17 years old were in the labor market; in 2008, this number was reduced to 10.2%. In 2008, approximately 51% of children in the labor market were working as domestic workers, and approximately 35%

worked in rural activities[18]. In 2009, there were still 4.25 million workers between 5 and 17 years old.

There are many empirical studies in the literature that observe the positive impact of an increased household income on reducing the incidence of child labor (see Basu and Tzannatos (2003) for a survey). Edmonds (2005) studies the impact of the impressive economic growth observed in Vietnam between 1993 and 1997 on the reduction in child labor and finds that the per-capita-income growth was responsible for reducing child labor by nearly 80% among households that experienced per-capita income improvements sufficient to move the family out of poverty.

Duryea and Arend-Kuenning (2003) question the idea that child labor is entirely driven by poverty. Their results demonstrate that after controlling for household characteristics, employment rates for 14-16-year-old boys and girls in urban Brazil increase as labor-market opportunities improve.

Emerson and Souza (2003) have focused on the dynamics of child labor and observe something they call the "child labor trap" – children who work receive less human capital and receive less income in the future; therefore, they will be more likely to send their own children to the labor market in the future, as well. These researchers examine the intergenerational persistence of child labor in Brazil, asking whether the child-labor status of parents affects the incidence of child labor among their own children. These researchers assess the intergenerational link created by financial need but also assess the intergenerational link "over and above that which is transmitted through the production of income (perhaps through social norms)". They find evidence of this link even after controlling for income. Another important result shows that children who did not work as child laborers earned higher wages in their adult lives, suggesting that the gains brought about by human capital and accumulated during childhood surpass the gains in experience acquired through apprenticeship.

A positive exogenous income shock could help to reduce child labor, providing the necessary resources for the family to send their children to school and not to the labor market. This idea drives conditional-cash transfer programs that reward children who are attending school (Bourguignon, Ferreira and Leite (2002)); however, this paper aims to

[18] Source: PNAD 2008 and 2009.

analyze whether an income shock (which is equivalent to a non-conditional cash transfer) would affect education and child labor.

Carvalho (2000) also investigates the impact of old-age benefits on child labor in Brazil and find a reduction in child labor by boys and girls. This paper, however, does not focus on the intra-household allocation model. Moreover, the identification strategy considers a control group based on the entire population not affected by the reform, and this approach could generate inconsistent estimators because of the heterogeneity of the treatment and control groups. As will be argued, the identification strategy proposed by this research will construct both control and treatment groups that include children living with elderly relatives; therefore, no heterogeneity among control and treatment groups will jeopardize the estimates.

The theory that underlies the empirical research in this paper is the classical theoretical structure, where we assume child labor occurs only because parents need the income to guarantee the children's survival. Child labor may occur not because of parents' attitudes but because poverty demands child labor for survival. The fact that children of the non-poor rarely work, even in very poor countries, supports this idea; however, this article does not attempt to deny that there might be other drivers of child labor.

Therefore, the main purpose of this paper is to address the impact of old-age benefits (income shock targeted to the elderly) on child labor and education in different income and socioeconomic quantiles in rural Brazil. Additionally, this work will investigate whether the gender of the beneficiary influences the results and whether boys and girls are affected differently. The results are especially important for policy-makers; if they show that income increases do not reduce child labor, then it may be necessary to adopt policies directly targeted to reducing child labor. Moreover, if an income shock to the family does not increase education levels, different targeted policies may also be preferable. The results would still contribute to knowledge of intra-household allocation models, as they would show whether an income shock targeting grandparents is likely to affect allocation of resources to children. Furthermore, learning whether old-age benefits can reduce the incidence of child labor and increase education would contribute considerably to the discussion about allocation of public resources among the elderly, comparing it to how much is allocated directly to children's education or to other social programs. Usually, governments are criticized for designing very expensive social-security systems. Although that is often the case, knowing whether the system creates positive externalities on child development in addition to protecting the elderly helps policy-makers to assess this issue.

2.3 Data

The data come from the Brazilian Household Survey PNAD (Pesquisa Nacional por Amostras de Domicílios), a sequential cross-section survey conducted on a regular basis since 1981 by IBGE (the Brazilian Census Bureau) that contains extensive information on the personal and household characteristics of all urban and almost all rural areas in Brazil, except the Amazon region. The sample size of PNAD equals 1/500 of the Brazilian population. This research uses the 1988, 1889 and 1990 surveys to construct the database for the years before the reform that took place in 1991. We use the 1992, 1993 and 1995 surveys to construct the database for the post-reform years[19].

Unfortunately, these surveys do not provide information about child labor for children younger than 10 years or specific information about domestic child labor. Therefore, the child labor results are restricted to the impact of income shock on children 10 years and older. Moreover, the results for girls may be compromised because most girls undertake domestic labor.

Our sample considers children living in rural households composed of a mix of adults, children and elderly members who are eligible or almost eligible for social-security benefits. Table 1 provides summary statistics.

2.4 Identification and Empirical Strategies

The identification strategy must consider that a family's unobserved characteristics might be correlated with family income and with family decisions about child labor and education. Therefore, a simple regression of child labor, for example, on

[19] In 1994, due to a budgetary crisis, IBGE did not conduct the survey.

variation in family income could capture the effect of the parents' backgrounds and intellects, both of which are correlated with income and with the families' decisions about sending their children to the labor market. The Brazilian social security reform provides an excellent opportunity to observe an exogenous income shock, which is necessary to obtain consistent estimates. This article considers the exogenous income shock generated by the reform to measure the significance of an unanticipated increase in pension income on child labor and educational attainment and also whether the effects depend on the pensioner's characteristics.

The empirical strategy considers a difference-in-difference estimator to identify the impact of the reform, where children affected by the reform (the treatment group) are compared with children not affected by the reform (the control group) before and after the reform; however, some problems could arise when constructing the treatment and control groups. For example, selectivity bias could arise, as the decision to apply for the benefit could be endogenous. Moreover, the benefit depends on past earnings, and the income from the benefit could be correlated with unobserved characteristics. To mitigate these issues, rather than use the actual treatment group, an *intent-to-treat* group that considers all of the eligible elderly will be created.

Additionally, families with elderly members may differ from families with no elderly members. The presence of an elderly person may be correlated with other unobserved variables that may also be correlated with child labor and the children's educational achievements. "Therefore, from one single cross-section, it is impossible to disentangle the direct income effect caused by old-age pension from the impacts of living with an elderly person. An exogenous reform in social security income variation; however, allows separating these effects" (Ponczek, 2011). Consequently, to use variation in social-security income among households to analyze the impact of income shock on child labor and educational achievements, we need to take these differences into account. For that reason, treatment and control groups will be composed of households with elderly individuals who are eligible and almost eligible for the program, respectively.

Therefore, the treatment group is composed of members of households with an eligible elderly person (under the new and old rules of the system), and the control group is composed of members of households with elderly members who are not old enough to be eligible (men between 55 and 60 years and women between 50 and 55 years). We believe that this strategy represents an important improvement over Carvalho (2000), as it can be used to build similar control and treatment groups, making our findings more robust and minimizing the heterogeneity between children living with an elderly family member and children with no elderly family member. Heterogeneity between the treatment group and a control group could jeopardize the consistency of the estimation if it were not properly addressed.

The impact of the social security reform on family income differs for families with a previously eligible member and families with a newly eligible member. The impact for those already receiving benefits was felt automatically after July 1991. Conversely, the impact for the newly eligible elderly was felt immediately after their decision to apply for the benefit. Moreover, for those families that have a newly eligible member who now receives the minimum benefit, the amount of the benefit received was zero before the reform and one minimum wage afterwards. Alternatively, for those who were already beneficiaries, the impact of the reform was half the value of the benefit of the newly eligible group; the benefit increased from ½ minimum wage to one minimum wage. For that reason, we consider four different treatment groups: two for men and women who were eligible under the old rules (minimum ages were 65 years for men and 60 years for women) and another two treatment groups for men and women who were newly eligible under the new rules (a man between 60 and 64 years and a woman between 55 and 59 years).

The difference-in-difference approach requires, for consistent results, that the temporal trend in the outcome of interest be the same for both the treatment and the control groups, before and after the reform. If the control group has a different temporal pattern from the treated group, the difference-in-difference estimator will be biased. The use of families with an almost-eligible person (a man between 55 and 60 years and/or a woman between 50 and 55 years) as the control group helps to disentangle the true treatment effect from the elderly relative effect. We believe that this assumption is reasonable. The reduction in the incidence of child labor in Brazil observed over time, as well as the improvements in education achievements, reinforce the importance of having a control group that is truly comparable to the treatment group for consistent estimates of the impact of the reform.

Moreover, we decided to construct the pre- and post-reform periods using three years of data for each period, as for those who became eligible after the reform or decided to apply after the change in rules, the entire registration process took several months, due to administrative delays. It is possible that newly eligible workers ignored the new rules of the system for a length of time, thereby affecting the proportion of new members who entered the system just after 1991. Therefore, we use datasets from 1992 to 1995 (the post-reform year range) to allow the inclusion process for the newly eligible to run its course.

Anticipation of benefits might interfere with our results. We could observe changes in the behavior of our control group if members anticipated that they would become eligible soon, but there was a severe credit constraint in the Brazilian economy during the 1980s and early 1990s—even more so among rural families; therefore, families would not anticipate benefit guarantees. Moreover, as observed by Ponczek (2011), "ignorance of pension benefits is another probable reason why those families do not bring this future income to the present". Edmonds (2006)[20] reaches a similar conclusion for South Africa, i.e., families that become eligible do not anticipate the future income and therefore do not experience changes in schooling before the income pension is available. He also argues that liquidity constraint is the most consistent explanation for his findings.

The model to be estimated is the following:

$$E\left[Y \mid T_k^j, Post, W\right] = \beta_0 + \sum_j \left[\sum_k \left(\beta_{1,k}^j T_k^j \right) \right] + \beta_2 Post + \sum_j \left[\sum_k \left(\beta_{3,k}^j T_k^j Post \right) \right] + W \cdot \gamma ,$$

[20] E. V. Edmonds. Child labor and schooling responses to anticipated income in South Africa. Journal of Development Economics, 81(2):386{414, December 2006. URL http://ideas.repec.org/a/eee/deveco/v81y2006i2p386-414.html.

where Y is one of the outcomes of interest (child labor, literacy, school attendance); T_k^j s are binary variables for the four different treatment groups with *j* = male, female and *k* = old rule, new rule – (1) children living with females eligible under the old rules, (2) children living with males eligible under the old rules, (3) children living with females eligible under the new rules, (4) children living with males eligible under the new rules; *Post* is a binary variable that represents the post-reform years; *W* is a vector of household and personal characteristics, such as age, age squared, gender, race, family size, number of children in the family; age, gender, race and education of the head and the oldest member of the family.

Considering this specification, the parameter of interest ($\beta_{3,k}^j$) is our difference-in-difference estimator. After estimating the old-age reform impact for families of all income levels, we separately estimate the same impact for families with different socioeconomic levels. For each socioeconomic level q (q = 1, 2, 3, 4, 5), we estimate

$$E\left[Y^q \mid T_k^j, Post, W^q\right] = \beta_0^q + \sum_j \left[\sum_k \left(\beta_{1,k}^{q,j} T_k^j\right)\right] + \beta_2^q Post$$
$$+ \sum_j \left[\sum_k \left(\beta_{3,k}^{q,j} T_k^j Post\right)\right] + W^q \cdot \gamma^q \quad ,$$

where we are interested in $\beta_{3,k}^{q,j}$ for the different *q*s.

We create a socioeconomic index level using principal-component factor analysis, based on the head of household’s education, occupation, sector of activity, family size, durable goods possession and family house’s characteristics, such as presence of sewage system and brick walls.

To determine the consistency of our estimates, we consider Two-Stage Least Square models, where we use the reform dummies as instruments for family income. The results from the first stage use the reform to predict family income, and the second stage estimates the effect of family income (instrumented) on child outcomes; however, this approach does not allow verification of whether the impacts depend on the pensioner’s characteristics (male or female, eligible under old or new rules of the system).

2.5 Results

Table 2 shows that the reform did have an important impact on family income. It presents the regression using the difference-in-difference strategy just described where the dependent variable is the log per-capita family income. We can observe that ex-ante, children living with eligible members belonged to families with smaller per capita income. The coefficients from the first column reveal that our identification strategy captures the income shock suffered by the families with eligible members, due to the social security reform. Treated families experienced significant income growth compared to their counterparts in the control group. The parameters ($\beta_{3,k}^{j}$) are all significantly different from zero. In addition, the impact of living with an eligible man ($\beta_{3,new}^{male}$) and ($\beta_{3,old}^{male}$) is not significantly different from the impact of living with an eligible woman ($\beta_{3,new}^{female}$) and ($\beta_{3,old}^{female}$), respectively. Additionally, even though we expected the magnitude of the income shock to be higher among new eligible members than among old eligible members, the coefficients of old eligible members (men and women) are significantly higher than the coefficients of new eligible members, which may be reflecting delays in new registrations to the system. Figure A1 in the Appendix shows how average family income behaved in the treatment and control groups before and after the reform.

Examining each income quantile, we did not always find that the reform caused significant income growth among treated families. One possible explanation is the disincentive that people from higher income groups have to apply for this kind of benefit, due to its relatively low value; however, an analysis of the impact of an income shock in different income quantiles might be problematic, as the shock might change families' positions in the distribution, jeopardizing the before-and-after comparison. For that reason, we prefer to analyze the effects on families from different socioeconomic positions. Treated families from all socioeconomic levels experienced significant income growth compared with their counterparts in the control group (Table 2).

Ponzeck (2011) also observes that the reform had no significant impact on adults' labor market outcome (e.g., employment and job search); "therefore, there is no evidence that extra income caused any reduction on the labor supply of those adults directly affected by the social security reform".

Table 3 contains the results of the difference-in-difference specification for child-labor outcomes[21]. The first column provides the results for the entire sample, and the next columns present the results for the different socioeconomic quintiles. Ex-ante, children living with newly eligible females are more likely to work than children living with elderly members of the control groups; however, after the reform, children living with the same newly eligible females are less likely to be working. To illustrate this point, we can see that children with a female from the new treatment group, $\beta_{3,new}^{female}$, are 4.8 percentage points less likely to work. As expected, children living within families with an educated male head of household are less likely to be working. Moreover, families with more children have a higher probability of sending their children to the labor market.

Tables 3a and 3b separate the results for girls and boys, revealing significant differences. Before the reform, girls living with already eligible males were less likely to be working. As we can observe, the income shock due to the social security reform seems to have had no impact in the occurrence of child labor among girls (Table 3a). Elderly females who are newly eligible for Social Security seem to use the new income for the benefit of their granddaughters, taking them out of the labor market, but this result is only slightly significant (10%). We believe that the reason for this mild impact on girls' child labor is the fact that our dependent variable "child labor" does not specifically consider domestic child labor, which is the activity performed by most of girls in the labor market. In addition, Table 3b reveals that social security reform seems to have had no impact in the occurrence of child labor among boys. Boys living with elderly females newly eligible for Social Security seem to be less likely to be working, but this result is significant only at 10%. For instance, the presence of a newly eligible female member

[21] In our sample of children between 10 and 14 years old, we have 2177 children in the treatment group (1) - children living with females eligible under the old rules, 2801 children in the treatment group (2) - children living with males eligible under the old rules, 2742 children in the treatment group (3) - children living with females eligible under the new rules, and 2026 children in the treatment group (4) - children living with males eligible under the new rules.

(*Female Treatment$_{new}$ x Post*) reduces by 4.3 and 5.6 percentage points the likelihood of having a girl and a boy working in the family, respectively.

Tables 4 and 5 analyze the difference-in-difference impacts on the education variables for children between the ages of 6 and 14 years in the rural area[22]. We focus on children in that age range because from 6 to 14 years, any child can complete the mandatory primary and secondary levels. The Brazilian constitution requires that municipalities provide primary education (up to 8 years of schooling), and states must provide secondary education (3 years of schooling); however, there are many costs—for transportation and school supplies, for example—other than tuition that might prevent children from going to school. Child labor is relatively common in rural areas; therefore, an income shock may have a positive effect on educational attainment variables. Table 4 shows the difference-in-difference estimates when literacy is the dependent variable. We observe that in general, ex-ante, children living with elderly members from treatment groups seem to be less literate than children living with elderly members from the control group, except for children living with females already eligible for Social Security. The "post" variable shows the positive trend in education attainments observed in Brazil during these years. The coefficients of the control variables are all significant and have the expected signs. Children living with families with a white, educated male head of household have higher literacy.

The difference-in-difference estimates reveal that living with an eligible male has a positive and significant impact on a child's literacy. For instance, the presence of a newly eligible male member (*Male Treatment$_{new}$ x Post*) increases by 5.0 percentage points the likelihood of literacy (Table 4). Children living with an already eligible male are 2.6 percentage points more likely to be literate but only at 10%. Curiously, the presence of any eligible female members does not seem to have any impact on the literacy level of children, in contrast to the usual findings in literature regarding this topic.

[22] Considering our sample of children between 6 and 14 years old, we have 3611 children in the treatment group (1) - children living with females eligible under the old rules, 4425 children in the treatment group (2) - children living with males eligible under the old rules, 4079 children in the treatment group (3) - children living with females eligible under the new rules, and 3097 children in the treatment group (4) - children living with males eligible under the new rules.

Dividing the sample into boys and girls (Table 4a and 4b), we find that only the literacy levels of girls living with eligible males is positively correlated with the income shock. Boys are barely benefited, as the impacts are positive but significant at only 10%.

Table 5 shows the difference-in-difference estimates when school attendance is the dependent variable. For the entire sample, we observe that ex-ante, children living with eligible members females are as likely to attend school as children living with members from the control group. The difference-in-difference estimates reveal that after the reform, living with an eligible male increased children's attendance. The presence of an eligible male under the new rule increases by 4.8 percentage points the likelihood of a child attending school after the reform. Eligible males under the old system's rule help to increase the attendance of grandchildren by 3.8 percentage points.

Tables 5a and 5b separate the results for girls and boys. The difference-in-difference estimates reveal that after the reform, living with a newly eligible male increases boys' and girls'[23] attendance; however, already-eligible females seem to benefit their granddaughters, increasing their school attendance by 6.5 percentage points (Table 5a).

In summary, we do not always find the same impacts of old-age benefits and income shock that are found in the literature. The studies devoted to such questions usually reveal that women have a preference for girls in the family, while men, when they exert some control over the children' education, tend to prefer boys; however, our estimates suggest that men also dedicate their additional income to the education of their granddaughters. One possible explanation is that men and women have different bargaining powers inside the family.

One question raised by such results is whether the impact of the income shock on children we find on average would be found if we focused on families with different income and socioeconomic levels. Would we confirm these results looking at families from the lowest income and socioeconomic levels or would we find something more similar to what is found in the literature about the subject? Therefore, aside from looking at the impact of the income shock on child labor, literacy and school attendance, this study raises the question of whether children living in families with different income

[23] The impact on girls in significant only at 10%.

levels would experience the same effects. The income shock might move families among the income quantiles, complicating analyses of the before and after shock impacts in different income groups. Therefore, the next step is to develop a socioeconomic index based on variables, such as education, occupation and durable goods possession, to separate families by their "wealth" and not by their income level.

A socioeconomic index (SES) was developed using principal-component factor analysis, considering variables like (i) possession of durable goods (TV, refrigerator, stove and water filter); (ii) type of house construction (which material was used on the walls); (iii) sewage system; (iv) education of head of household; and (v) labor-market characteristics—such as occupation and sector of activity—of head of household. We also developed a second SES that considered only the first four items of the previous SES.

The analysis of the first socioeconomic index[24] shows that the impacts are concentrated at the lowest SES quintile. Moreover, the results suggest again that a man might have more bargaining power inside the family, which would explain some of the differences in the results found in the literature. When looking at all children together, we generally confirm that the old-age benefits paid to a man help to increase child literacy and attendance, and we find that such impact is concentrated in the lowest socioeconomic quintile. A female's impact on child labor is also concentrated in the first socioeconomic index quintile.

If we consider girls separately, again we observe that the female's impacts on child labor and attendance are concentrated in the first socioeconomic index quintile. Additionally, elderly men who benefited under the new rules and old rules of the system exert a positive impact on the literacy and attendance of their granddaughters in the lowest quintile.

Considering the impact on boys, although we do not find on average that elderly men's benefits are partially allocated to improve boys' education, we observe that this outcome is not what is observed among families from the lowest socioeconomic quintile. Elderly men from the lowest quintile exert a positive impact on attendance of their

[24] A different definition of socioeconomic index produces similar results.

grandsons. The only result that puzzles us is the positive and significant impact of female elders on boys' child labor in the top socioeconomic quintile.

Table A1 in the Appendix shows Two-Stage Least Square estimates, where we use the social security reform dummies as instruments for family income; however, as this approach does not allow us to verify whether the impacts depend on the pensioner's characteristics (male or female, eligible under old or new rules of the system), we not always find the same results as those observed above. The income shock seems to have a positive impact only on girls' school attendance. The previous approach revealed that girls' attendance increased for girls living with both eligible males and females; therefore, the two-stage least-square approach captures all of these impacts.

Some may question the adopted strategy, arguing that we could observe changes in the behavior of our control group because they would anticipate that they would become eligible soon. As mentioned, the main reason that we are comfortable saying that this would not be a problem is because there was severe credit constraint in the Brazilian economy during the 1980s and early 1990s. This constraint would be even more severe among rural families. Moreover, ignorance of pension benefits is another probable reason why those families do not bring this future income to the present.

To investigate the adequacy of our identification strategy and our control group, we construct a false treatment group composed of previous control groups (women aged between 45 and 50 years and men aged between 55 and 60 years) and compare them with a new younger control group (women aged between 40 and 45 years and men aged between 50 and 55 years). If the original control group would anticipate their entrance into the system and change their behavior, we would observe, in the regression just described, a different impact for children living with the new (false) treatment group compared with the new (younger) control group; however, Table A2 in the Appendix does not show such a difference.

Finally, we further examine if our results favoring those children living with eligible males are motivated by differences in the bargaining power of men and women within Brazilian families, as was formerly observed. To investigate that problem, we perform two separate regressions, with one considering children living within families with male heads of household and the other considering only children living with female heads of household. When observing children living with male head of households, eligible males exert the same positive impact on literacy and attendance as described above; however, the same is not true when we look at children living with female heads of household. On the other hand, we observe that the presence of an eligible female head explain the positive impact on boys' child labor and girls' attendance, as shown in Table A3 in the Appendix.

Therefore, such results support the idea that bargaining power differences between men and women within households explain the uneven effects for children living with eligible males and eligible females.

2.6 Final Remarks

The income shock experienced by rural Brazilian families after the 1991 reform resulted in an improvement in the educational attainments of children living with eligible males. Moreover, eligible females helped their grandsons to leave the labor market in cases of child labor. The analysis of the socioeconomic index shows that the impacts are concentrated in the lowest SES quintile.

We do not always find the same impacts of old-age benefits and income shocks that are found in the literature. The studies devoted to such questions usually reveal that women have a preference for girls in the family, while men, when they exert some control over their children's education, tend to prefer boys; however, our estimates suggest that men also dedicate their additional income to the education of their granddaughters. The analysis of the impacts on different socioeconomic levels confirms these results. One possible explanation is that men and women have different degrees of bargaining power inside the family. On the other hand, female heads of household seem to favor their grandsons in cases of child labor and to invest in their granddaughters' education, as well.

Such results suggest the idea that bargaining power differences between men and women within the household explain the uneven effects for children living with eligible males and eligible females.

Chapter 3

Student Proficiency and Teacher Effect: Impact on Students with Different Levels of Achievement

Priscila Pereira Deliberalli

3.1 Introduction

The literature on the economics of education has shown that family background is decisive in determining children's educational attainment. Nevertheless, such findings should not be interpreted to mean that schools and teachers play only a minor role in children's school performance. The recent literature has shown that schools and teacher quality explain an important part of children's educational development as well; however, these findings usually do not test whether teacher contribution is the same for students with lower initial test scores and those with higher initial test scores. Therefore, this study will test whether teachers are more or less important in helping student test scores to improve when students have poor test scores initially.

The reform of the public education system has played a major role in policy debates in Brazil over the last several years, especially after the universalization of standardized student-achievement evaluations. The disappointing performance of students on language and mathematics tests and the gap between students from public and private schools on most measures of academic achievement have worried parents and policymakers, increasing the pressure to restructure the entire system. Nearly everyone involved in the education process recognizes the importance of teacher quality to student achievement. School administrators and policymakers, aware of such connections, have established some criteria for hiring high-quality teachers, aiming to improve student proficiency progress. Therefore, it is crucial to have adequate measures of teacher quality; however, little is known about how teachers affect different kinds of students, and this lack of knowledge is especially worrying when the public school system decides to implement accountability programs using student achievement in teacher assessment and placing achievement-related accountability pressure on individual teachers and schools.

The measure of the impact of teacher quality on students is not straightforward, as we cannot simply compare groups of students from different teachers. The school performance of a group of students would depend, besides the quality of its teacher, on (i) the starting knowledge levels of students, (ii) their endowments (abilities and family backgrounds), and (iii) the teacher's working condition, for example, the school's infrastructure. Therefore, any theoretical model and empirical strategy need to account for these problems when attempting to measure the effect of teacher quality on student school performance. Part of this heterogeneity in student and teacher working conditions can be controlled by including observed characteristics of the students, families, and schools, but most studies include fixed effects to control for at least the time-invariant heterogeneity. Therefore, the objective of empirical analysis is to obtain estimates of differences in teacher contributions to student-learning progress that eliminates the major sources of possible confounding from student heterogeneity or teacher-assignment practices.

To evaluate teacher contributions to student achievement, value-added models have been used to isolate teacher contributions to student performance based on previous student proficiency levels and individual background. If a theoretical model does not control for the history of past inputs and individual endowment (student achievement as a function of contemporaneous factors only), it poses serious omitted variable problems. Conversely, value-added models are susceptible to endogeneity bias when certain important inputs are missing, as they include lagged achievement measures. Although analysis using value-added models evaluates whether a teacher does a better job than the others of improving student test scores than do other teachers, these analyses usually do not signal if teacher's contribution is the same for students with lower and higher starting test scores Therefore, this study will analyze whether teachers are more or less important in helping students to improve test scores when students have poor past test performances. The analysis will be based on value-added measures of student achievement in the São Paulo school district, which is the largest school district in Brazil.

The results reveal that low-achieving students exposed to better-quality teachers[25] would expect to achieve 0.61 and 0.60[26] standard deviations higher in Portuguese and mathematics test-score performances. At the same time, high achieving students have Portuguese and mathematics scores increased by 0.57 and 0.73 standard deviations when exposed to better quality teachers; however, such impact represents a larger proportion of the average test score gains for high-achieving students. Moreover, if we analyze the impact of teachers on different students inside the same classroom, we also observe that students in the top of the test score distribution benefit more from better quality teachers.

3.2 Literature

Several studies have attempted to identify teacher effects on student achievement. Most of these studies have attempted to investigate the relationship between teacher credentials, teacher quality, and student achievement to provide information to policymakers about criteria for hiring and policies to raise the quality of teachers. These studies usually reveal that most observable teacher characteristics – such as schooling and experience – have a weak relationship with student performance. Such analyses demystify some beliefs showing, for example, that teacher experience helps to improve student proficiency only up to a certain point and that higher educational degrees, such as Master's degrees and PhDs, do not necessarily contribute to student advancement; however, these findings cannot be interpreted to mean that teacher quality does not influences student achievement. Instead, this finding means that other unobservable teacher characteristics may explain most of teacher heterogeneity. As teacher quality is driven by characteristics that are difficult to measure, teacher quality measures have to be based directly on student performance.

Rockoff (2004) includes student fixed effect to control for previous student knowledge and also to control for differences in the potential learning capacity of each student. This study compares teachers in the same school to control for working conditions and school characteristics impact. The author argues that "observing the same

[25] One standard deviation increase in teacher quality.
[26] Grades are normalized by year and grade.

teacher with multiple classrooms allows me to differentiate teacher quality from factors like class size. In addition, by focusing on variation in student achievement within particular schools and years, I separate variation in teacher quality from variation in school-level education inputs and time-varying factors that affect test performance at the school level". The results reveal that a one-standard-deviation increase in teacher quality increases student test scores by approximately 0.1 standard deviations in reading and mathematics.

Clotfelter et al. (2007) use end-of-course test scores in multiple subjects to analyze the relationship between teacher credentials and student achievement in high school, estimating student fixed-effect models in the context of a model estimated across subject, rather than fixed effect in a model estimated over time. Student fixed effect helps to mitigate the nonrandom distribution of students among classrooms and teachers. These researchers' results reveal that teacher credentials affect student achievement systematically at the high school level, as on average, students exposed to teachers with weak sets of credentials would expect to achieve 0.3 standard deviations lower than students exposed to teachers with strong sets of credentials. Moreover, having a teacher with strong credentials could on average even offset adverse effects of racial and socioeconomic differences among students.

While several studies try to estimate the relationship between teacher characteristics and attributes and their impact on student achievement, Grossman et al. (2010) try to observe what instructional practices differentiate teachers with high value added from teachers with low value added to students. The authors believe that "teachers' classroom practices are likely to be the mechanism by which teachers affect students" and the knowledge of the "classroom practices that are more characteristic of more effective teachers" provides policymakers tools for improving the quality of education for all students. , These authors' results reveal that teachers at the top of the value-added distribution score higher in all elements of instruction practices observed and that these differences are statistically significant for an important subset of practices.

Aaronson, Barrow, and Sander (2007) use quasi-value-added models (controlling for student performance in t – 1) to control for previous student knowledge. Moreover, these researchers control for other student and family characteristics to capture differences in the potential learning capacity of each student. These authors compare teachers in the same school when those schools have identical observable characteristics. The analyses find that studying with a teacher two standard deviations higher in quality could add 25% to 45% of an average school year to student mathematics performance. Moreover, the authors stratify the students into ability groups and find that “a two standard deviation improvement in teacher quality is still worth a sizable gain in average test score growth, particularly among the middle and low achieving population”.

Buddin (2010) observes that “teacher experience and educational background have weak effects on teacher effectiveness. Teacher experience has little effect on (…) scores beyond the first couple of years of teaching (…) and teacher education beyond a bachelor’s degree has no statistically significant effect”. Moreover, the authors suggest that “teachers with better prepared students have some small advantage in measured effectiveness. A one standard deviation in the mean ELA (English Language Arts) and mathematics scores of teacher’s new students is associated with about a 0.03-point increase in the teacher’s value added”. The objective of this study is to analyze this subject further.

3.3 Empirical Strategy

To measure the impact of teacher quality on student school performance, we have to manage certain methodological obstacles and data limitations. As Todd and Wolpin (2003) note, “ideally, model estimation requires a comprehensive history of all past and present family and school/teacher inputs as well as information about each student’s endowed ability. This complete information is not available; however, leading to potential biases due to student unobserved heterogeneity, teacher unobserved heterogeneity and nonrandom assignment of students to particular teachers”. Therefore, we cannot simply compare groups of students from different teachers and explain such differences based on their teacher performances. The educational achievements of students would depend on other factors besides the quality of their teacher. First, teachers have students with different starting knowledge levels, and therefore the comparison of those students’ final levels of proficiency will be compromised. If students with higher starting knowledge levels are allocated to better teachers, then we will overestimate the effects of teacher quality when comparing these students with students from lower quality teachers. To manage this problem, the models estimated must account for the initial heterogeneity in student proficiency , which can be accomplished by estimating the impact of teachers on the proficiency acquired while studying with that teacher (value-added models) or by specifically controlling for the initial proficiency level (quasi-value-added models).

Second, students may have different learning capacities and endowments (abilities and family backgrounds). Ideally, students should be randomly allocated to teachers such that teachers have students with the same capacities and endowments. Nevertheless, that allocation is not usually the case. We can only partially account for these differences when controlling for the initial proficiency levels, as two students with the same initial knowledge may end up with different proficiency levels at the end of one year in the same class with the same teacher; however, certain student and family characteristics may predict such learning capacity differences. Therefore, the model estimated should also include student and family characteristics.

Third, to access the impact of teachers on student performance, ideally we have to compare teachers with the same working conditions, such as school infrastructure. The literature about empirical education production function and teacher quality always emphasizes the importance of school-level factors, such as school size and composition, principal characteristics, and curriculum. If better-quality teachers work in schools with characteristics that may positively influence student performance, then we would overestimate the effect of teachers; however, as our estimates are based on achievement gains, we would only be concerned if there were changes in such school factors during the three-year period analyzed.[27]

Our concern in estimating teacher quality is whether there is nonrandom sorting when placing students with certain teachers. However, informal discussions with São Paulo school district representatives suggest that the process is not based on student characteristics, and there is no parental influence on teacher selection.

[27] Some researchers use school fixed effects to control for time invariant school differences and, as a result, they compare teachers in the same school; however, we tried to run a school fixed-effect model, but as many teachers work in only one school, several teacher dummies were excluded from such regression.

The main purpose of this research is to analyze if the teacher effect may change with different student populations (based on their students' initial knowledge), i.e., the teacher effect may be different for a student who is still in the bottom of the test score distribution than for a student who is already in the top of the distribution. Therefore, we stratify the sample into ability groups based on the previous year's test score performances and estimate the teacher effect within ability group. The quasi-value-added model estimates, where the impact of lagged schooling, family background, and other characteristics are captured in the lagged test score measure, is as follows:

$$T_{it}^{l} = X_{it}^{l}\alpha + \gamma T_{it-1}^{l} + \beta u_{i}^{l} + \sum_{1}^{j-1} \lambda^{l}{}_{j}\, p^{l}{}_{j} + \eta_{it}^{l} \ , \qquad (1)$$

where

X_{it} would include such variables as classroom characteristics (class size, peer composition – proportion of female and white students)

u_i would include such variables as student's gender, race, and parents' education

p_j are dummies for teachers

η_{it} contains time variant student and teacher unobserved characteristics

l represents the different ability groups.

We run regressions separately for the different *l* proficiency level or ability groups. The *l* ability groups are stratified in two different ways. First, we consider the whole distribution of students and separate them into low-, medium-, and high-achievement student groups. Students in the bottom 25% of the previous year's test score distribution are considered low-achieving students; students in the top 25% of the same distribution are considered high-achieving students; the remainders are considered medium-achievement. Therefore, students in the bottom (top) of the distribution will be students with low (high) nominal values of proficiency level; however, when comparing teacher effect on these different groups, we would not be comparing the same teachers necessarily. As Aaronson, Barrow, and Sander (2007) observe, "looking at subgroups of students with more similar initial test scores should help reduce the possibility that teacher effect estimates are simply measuring test score growth related to normalization issues”.

Second, we stratify the sample into *l* ability groups inside each classroom into four groups. The idea is to analyze if the “same” teacher may have a different impact on different students inside the classroom, i.e., whether students that are in a relatively lower branch of the distribution are benefited equally by a better teacher. Consequently, students in the lower (top) group will not necessarily have low (high) proficiency levels, but they are the worst (best) students of each teacher. This procedure guarantees that we will be comparing the same teachers across the different groups.

Parental characteristics influence neighborhood and school choices, which could cause some potential bias. Nevertheless, Brazilian families’ decisions about where to live are normally based primarily on income level; families do not decide where to live based on the quality of the public-school system. In general, low-income students attend public schools near their homes, and their families’ decisions about where to live do not consider school quality, only the ability to afford to live in the neighborhood. The covariate “father’s education” partially controls for family income and therefore for the choice of neighborhood.

Kaine and Staiger (2002) note that the variance in the estimate of teacher effect may be inflated by sampling variability. To attenuate this problem partially, we restrict our sample to students with teachers who had at least 10 students per year. The final regressions include year dummy variables, as well.

3.4 Data

The pressure to improve the quality of public education has led certain Brazilian states and cities to apply their own standardized achievement tests to measure the performance of their schools. Such tests have enabled the creation of a database with individual student identifiers, linking students with teachers and schools and allowing us to track student progress over time. The current study will be based on São Paulo’s public school students, who were followed for three years from 2007 to 2009. The sample will follow only students from the second through the fourth grade, as students in higher grades have more than one teacher, which would make it more difficult to isolate the teacher effect.

Table 1 contains summary statistics. We have information for approximately 11,000 students in 2008 and 2009. When in the third grade (2008), the students are, on average, 9.6 years old, and in the fourth grade (2009), they are 10.6 years old; 46% of them are female, and 40% are white. Their fathers have, on average, little more than four years of education.

Teachers may enter and exit the data set, but teacher effects are only identified by students who change teachers (from year to year). The sample has students for whom we have grade information for at least two years.

3.5 Results

Student test scores in Portuguese and mathematics are standardized by grade and year. We consider only students in the third and fourth grades, as after the fourth grade, students have more than one teacher per year. The impact of student X's covariates is based on the variation in X across students for each specific teacher. Certain student characteristics have a significant effect on achievement level, even after controlling for student test scores in the previous year. Therefore, learning progress seems to be influenced by some student characteristics aside from the teacher quality. Table 3 reveals that female and white students have advantages over the other students. The father's education level also helps yield higher student proficiency. Class size does not seem to have any impact on growth in student proficiency; however, if we do not restrict our sample to classrooms with at least 10 students, class size seems to matter for teaching mathematics.[28] Peer gender does not help to explain grade evolution, but peer race seems to matter to progress in language proficiency.

The dispersions in teacher quality are similar if we include peer characteristics; therefore, we decide to consider specifications (II) for language and (IV) for mathematics in Table 3. The results imply that a one-standard-deviation improvement in teacher

[28] See Appendix for results.

quality produces on average a 0.38 standard deviation gain in language test scores and 0.42 gain in mathematics test scores. Remember that the test scores are standardized.

We are particularly interested in analyzing the teacher effect on different student populations, especially on those achieving at the lowest and highest levels. We stratify the sample into ability groups based on Portuguese and mathematics test scores from the previous year and subsequently estimate the teacher effect within low and high ability groups. Low-ability students are those who had scores in the bottom 25% of the grade distribution, and high-ability students are those who had scores in the top 25% of the same distribution. The low-ability students have mean Portuguese and mathematics scores of 113.1 and 122.9, respectively, in the third grade and means of 126.1 and 139.1 in the fourth grade. Considering high ability students, mean Portuguese and mathematics scores are 185.9 and 198.9, respectively, in the third grade and 216.4 and 223.6 in the fourth grade. The results in Table 4 show that a one-standard-deviation increase in teacher quality raises Portuguese score performances by 0.61, 0.48, and 0.57 for low, medium, and high achievement students; however, such impact represents a bigger proportion of the average test score increase for high achievement students than for low achievement students. The same results are observed for mathematics scores where a one-standard-deviation increase in teacher quality raises mathematics score performances by 0.60, 0.51, and 0.73 for low, medium, and high achievement students, which also represents a larger proportion of the average test score growth for high achievement students.

The above mentioned results show that the teacher may have a stronger impact on high-achieving students; however, we would like to analyze whether the same teacher also has a different impact on students in the bottom of the classroom distribution compared to those students in the top of the proficiency distribution in the same classroom. This stratification permits us to compare the same teachers, as all of them will have students in the bottom and the top of the classroom distribution. Table 5 shows that students in the top of the classroom distribution would benefit more from a better quality teacher. Having a one-standard-deviation increase in teacher quality raises Portuguese score performances by 0.51 and 0.66 standard deviations for students in the bottom and the top of the distribution, respectively. However, again, as students in the top of the distribution have a smaller average test score increment, the teacher's impact represents a higher proportion of achievement progress. Considering the impact of teachers on mathematics performance, a one-standard-deviation increase in teacher quality raises student test scores by 0.54 and 0.78 standard deviations for students in the bottom and the top of the distribution, respectively. In this study, the impact of a better quality teacher is significantly higher for those students in the top of the classroom distribution.

Table 5 also shows a Chow's Test in which we analyze whether the explanatory variables have different impacts on different subgroups of the sample. The results reveal that the subgroups of students in the bottom and the top of the distribution are differently affected by the independent variable, including the teacher dummies, compared to the rest of their classmates.

3.6 Conclusion

Reforming the public education system has played a major role in policy debates over the last several years, especially after the universalization of standardized student-achievement evaluations, which revealed the disappointing performance of students on language and mathematics tests and the gap between students from public and private schools on most measures of academic achievement. School administrators and policymakers, aware of such findings, have established new criteria for hiring high-quality teachers, aiming to improve student progress. Therefore, it is crucial to have adequate measures of teacher quality. This lack of knowledge is principally worrisome when the public school system implements accountability programs using student achievement in teacher assessments and placing achievement-related accountability pressure on individual teachers and schools.

These results bring two important pieces of information to policymakers and school administrators. First, high-achieving students benefit more easily from high-quality teachers than do low-achieving students. Therefore, policymakers and school principals should act even more strongly concerning better training for or general improvement of teachers who teach low-achieving students.

Second, teacher-reward policies based on student performance evaluations must account for these different impacts on students. As many observable characteristics are not related to teacher quality, reward policies must be based on the relationship between teacher and student performance.

TABLES AND CHARTS

Chapter 1 Tables and Charts

Table 1.1 – Summary Statistics

	All Sample (%)	Formal (%)	Informal (%)
Age (years)	36.97	36.30	37.68
Female	41.89	38.95	45.03
Male	58.11	61.05	54.97
Married	63.63	64.68	62.51
White	51.51	58.21	44.40
Education			
less than 1 year	6.53	3.50	9.75
between 1 and 4 years	22.05	16.37	28.09
between 5 and 8 years	29.35	26.33	32.56
between 9 and 14 years	34.09	41.93	25.77
15 years or more	7.98	11.87	3.84
Region			
North	10.47	7.67	13.45
Northeast	26.35	20.80	32.23
Southeast	34.37	39.27	29.16
South	17.91	21.82	13.74
Middle-west	10.91	10.43	11.41
Metropolitan area	44.82	48.57	40.85
Ocupation			
Managers	6.51	9.06	3.80
Scientists and artists	5.74	7.31	4.08
Technicians	7.39	9.17	5.50
Services	25.67	22.61	28.92
Salesman	14.11	9.71	18.79
Industry employees	32.07	28.76	35.58
Administrative services	8.40	13.26	3.24
Other ocupations	0.07	0.09	0.04
Sector			
Industry	18.69	22.70	14.44
Construction	9.60	5.30	14.16
Retail	24.73	22.73	26.84
Food and Lodging	5.22	4.07	6.44
Transport and Communication	6.73	7.56	5.85
Public Administration	2.45	3.87	0.95
Health and Education	7.35	10.95	3.52
Housekeeping	10.66	6.31	15.28
Other sectors	14.57	16.51	12.51
On leave	1.76	2.51	0.97
No activity for health reasons	5.87	5.14	6.65
Health condition			
Excellent	22.40	25.87	18.71
Good	56.27	57.38	55.09
Regular	18.97	15.26	22.91
Poor	1.99	1.24	2.78
Very poor	0.36	0.24	0.50

Table 1.2 – Probability to receive treatment (formal worker)

	Prob (Formal)		
	All Sample	Female	Male
age	0.060	0.062	0.057
	(30.79)***	(19.30)***	(22.65)***
age_sq	-0.001	-0.001	-0.001
	(-32.97)***	(-20.54)***	(-24.86)***
white	0.048	0.067	0.041
	(5.24)***	(4.67)***	(3.42)***
female	-0.361		
	(-36.14)***		
education	0.061	0.052	0.066
	(47.65)***	(24.94)***	(40.10)***
married	0.0549	-0.124	0.215
	(5.94)***	(-9.26)***	(16.27)***
North	-0.32	-0.414	-0.273
	(-17.87)***	(-14.34)***	(-11.89)***
Northeast	-0.247	-0.314	-0.209
	(-16.57)***	(-13.32)***	(-10.79)***
Southeast	0.183	0.118	0.229
	(12.76)***	(5.23)***	(12.23)***
South	0.267	0.238	0.292
	(16.46)***	(9.42)***	(13.70)***
metropolitan area	0.136	0.157	0.117
	(15.94)***	(11.89)***	(10.36)***
managers	-0.420	-0.300	-0.416
	(-17.66)***	(-8.20)***	(-12.63)***
scientists and artists	-0.869	-0.751	-0.883
	(-35.35)***	(-22.38)***	(-24.03)***
techinicias	-0.735	-0.556	-0.766
	(-33.00)***	(-16.70)***	(-24.24)***
services employees	-0.435	-0.548	-0.258
	(-21.75)***	(-19.50)***	(-8.78)***
salesman	-0.994	-1.12	-0.877
	(-47.12)***	(-36.84)***	(-28.28)***
industry employees	-0.836	-0.871	-0.705
	(-41.72)***	(-24.42)***	(-25.21)***
other ocupations	-1.28		-1.215
	(-8.20)***		(-7.56)***
civil construction sector	-0.846	-0.003	-1.015
	(-49.44)***	(-0.03)	(-53.71)***
retail sector	-0.359	0.023	-0.552
	(-23.39)***	-0.7	(-30.29)***
food and lodging sector	-0.7	-0.354	-0.938
	(-30.52)***	(-9.41)***	(-30.30)***
transport and communication sector	-0.264	0.24	-0.456
	(-14.15)***	(4.10)***	(-21.91)***
public administration sector	0.429	0.634	0.276
	(13.31)***	(12.00)***	(6.57)***
health and education sector	0.214	0.437	-0.0691
	(9.88)***	(13.18)***	(-1.87)

Table 1.3 – Demographic characteristics

(%)	All Sample	block 1	block 2	Probability(Formal) block 3	block 4	block 5
Obs	106984	9390	27160	29916	27590	12903
on leave	1.76	1.51	1.60	1.76	1.93	1.89
formal	51.50	13.27	29.97	50.82	70.75	85.00
age (years)	36.97	42.83	37.35	36.26	35.83	35.96
white	51.51	23.57	37.46	51.72	63.50	75.35
female	41.89	52.58	49.97	41.11	33.90	36.02
education (years)	7.58	2.69	5.32	7.58	9.58	11.65
married	63.63	56.96	61.47	64.84	65.72	65.77
North	10.47	26.73	15.14	9.39	5.16	2.69
Northeast	26.35	56.60	35.41	25.08	16.70	8.80
Southeast	34.37	6.78	26.84	35.25	43.16	49.44
South	17.91	2.16	9.68	17.67	25.15	31.78
Middle-west	10.91	7.72	12.94	12.62	9.83	7.29
metropolitan area	44.82	28.15	37.45	44.98	50.88	59.13
managers	6.51	0.47	1.03	3.96	10.96	18.80
scientists and artists	5.74	0.81	1.86	4.96	9.42	11.45
techinicians	7.39	0.60	2.29	7.49	13.52	9.72
services employees	25.67	30.64	33.84	28.23	20.03	11.02
salesmans	14.11	30.00	23.91	15.80	3.78	0.12
industry employees	32.07	37.44	36.97	37.72	31.14	6.73
other ocupations	0.07	0.00	0.01	0.05	0.16	0.11
administrative services	8.40	0.04	0.10	1.76	10.96	41.86
industrial sector	18.69	2.81	8.02	19.59	29.45	27.64
civil construction sector	9.60	32.73	19.68	5.40	0.78	0.12
retail sector	24.73	25.23	28.66	29.45	20.94	13.24
food and lodging sector	5.22	9.20	7.33	6.27	2.94	0.36
transport and communication sector	6.73	0.91	4.51	8.60	8.91	6.63
public administration sector	2.45	0.01	0.06	0.70	3.31	11.52
health and education sector	7.35	0.10	0.22	2.97	11.94	27.98
house-keeping	10.66	26.37	23.56	8.32	0.15	0.00
other sectors	14.57	2.65	7.98	18.71	21.60	12.52
Excellent health	22.40	12.10	16.11	21.45	27.38	34.69
Good health	56.27	51.30	55.76	57.67	57.46	55.17
Regular health	18.97	30.72	24.72	18.79	13.94	9.48
Poor health	1.99	5.03	2.88	1.76	1.02	0.51
Very poor health	0.36	0.83	0.53	0.33	0.18	0.13

block 1: 0.0 < prob(formal) < 0.2
block 2: 0.2 ≤ prob(formal) < 0.4
block 3: 0.4 ≤ prob(formal) < 0.6
block 4: 0.6 ≤ prob(formal) < 0.8
block 5: 0.8 ≤ prob(formal) < 1.0

Table 1.3a – Demographic characteristics – Females

(%)	FEMALE	Probability(Formal) block 1	block 2	block 3	block 4	block 5
Obs	44820	5193	14076	11697	8020	5821
on leave	1.96	1.08	1.73	2.06	2.46	2.41
formal	47.87	10.80	31.28	50.35	70.45	84.93
age (years)	36.69	42.37	37.14	35.82	35.40	34.09
white	52.42	23.47	39.90	61.49	62.04	77.10
female	-	-	-	-	-	-
education (years)	7.96	3.02	6.03	8.43	10.80	12.14
married	55.39	59.68	58.67	55.29	53.43	46.52
North	9.84	27.96	12.08	4.48	7.77	1.91
Northeast	26.69	57.85	33.30	13.96	26.82	8.30
Southeast	34.70	6.74	30.95	43.35	36.08	49.42
South	18.14	2.04	9.63	28.30	19.19	31.23
Middle-west	10.62	5.41	14.04	9.91	10.14	9.14
metropolitan area	45.50	28.23	39.34	49.56	52.17	58.41
managers	4.97	0.12	0.40	3.37	13.68	11.56
scientists and artists	7.11	0.94	1.81	6.59	15.27	15.22
techinicians	7.02	0.12	0.63	4.59	21.12	14.09
services employees	40.37	54.84	57.76	43.94	20.02	6.29
salesmans	16.38	33.49	24.20	17.88	1.30	0.00
industry employees	12.53	10.46	15.13	21.29	5.64	0.02
other ocupations	0.00	0.00	0.00	0.00	0.00	0.00
administrative services	11.59	0.04	0.08	2.34	22.89	52.76
industrial sector	16.57	10.94	15.92	24.94	14.90	8.62
civil construction sector	0.41	0.10	0.17	0.35	0.86	0.74
retail sector	21.64	25.84	22.63	22.15	18.55	18.74
food and lodging sector	6.39	10.46	7.95	7.81	3.43	0.24
transport and communication sector	1.60	0.02	0.13	0.82	3.22	5.91
public administration sector	2.35	0.00	0.07	0.91	4.45	9.91
health and education sector	13.07	0.10	0.46	4.70	30.16	48.43
house-keeping	23.60	48.24	43.04	17.06	0.21	0.00
other sectors	14.37	4.31	9.62	21.26	24.21	7.40
Excellent health	20.80	10.63	14.83	22.02	26.30	34.31
Good health	55.22	49.28	54.39	57.23	57.24	55.68
Regular health	21.29	33.72	27.15	18.83	15.16	9.45
Poor health	2.23	5.39	2.97	1.61	1.10	0.40
Very poor health	0.45	0.98	0.65	0.31	0.17	0.17

block 1: $0.0 < \text{prob(formal)} < 0.2$
block 2: $0.2 \leq \text{prob(formal)} < 0.4$
block 3: $0.4 \leq \text{prob(formal)} < 0.6$
block 4: $0.6 \leq \text{prob(formal)} < 0.8$
block 5: $0.8 \leq \text{prob(formal)} < 1.0$

Table 1.3b – Demographic characteristics – Males

(%)	MALE	block 1	block 2	Probability(Formal) block 3	block 4	block 5
Obs	62164	4884	13461	16908	18126	8771
on leave	1.62	1.88	1.52	1.60	1.63	1.61
formal	54.11	15.40	28.85	50.84	71.06	85.69
age (years)	37.16	42.12	37.51	36.66	36.27	36.70
white	50.85	23.20	36.77	48.08	60.37	73.59
female	-	-	-	-	-	-
education (years)	7.31	2.49	4.96	7.04	8.86	10.95
married	69.57	58.01	64.61	69.12	72.23	79.02
North	10.93	25.90	16.54	11.72	6.06	2.50
Northeast	26.09	54.34	36.78	28.64	17.27	7.29
Southeast	34.13	7.25	24.45	31.48	42.22	52.31
South	17.74	2.13	9.69	14.34	24.02	32.37
Middle-west	11.11	10.38	12.53	13.81	10.43	5.54
metropolitan area	44.34	27.46	36.74	43.55	49.23	56.78
managers	7.62	0.76	1.63	4.76	10.61	19.96
scientists and artists	4.76	0.84	1.68	4.14	7.51	7.15
techinicians	7.65	1.64	4.75	8.95	10.24	7.62
services employees	15.07	2.62	8.72	17.67	20.85	14.84
salesmans	12.48	23.34	22.14	16.16	4.78	0.44
industry employees	46.16	70.76	60.89	46.88	39.47	22.23
other ocupations	0.12	0.00	0.01	0.08	0.23	0.17
administrative services	6.10	0.04	0.17	1.34	6.27	27.37
industrial sector	20.23	0.80	2.77	13.16	31.67	47.79
civil construction sector	16.22	64.56	38.86	9.05	0.88	0.08
retail sector	26.95	22.32	34.11	37.22	21.87	9.21
food and lodging sector	4.38	6.96	5.91	6.12	2.94	0.19
transport and communication sector	10.42	2.42	9.19	14.16	11.89	6.52
public administration sector	2.53	0.04	0.06	0.57	2.93	10.66
health and education sector	3.22	0.10	0.15	1.15	4.71	10.58
house-keeping	1.33	0.84	2.29	2.11	0.67	0.00
other sectors	14.72	1.97	6.66	16.44	22.43	14.96
Excellent health	23.55	13.88	17.66	22.08	26.92	33.84
Good health	57.03	54.22	57.24	57.75	57.83	55.22
Regular health	17.29	26.54	22.00	18.15	13.98	10.11
Poor health	1.82	4.75	2.62	1.75	1.03	0.73
Very poor health	0.30	0.57	0.47	0.27	0.22	0.09

block 1: $0.0 < \text{prob(formal)} < 0.2$
block 2: $0.2 \leq \text{prob(formal)} < 0.4$
block 3: $0.4 \leq \text{prob(formal)} < 0.6$
block 4: $0.6 \leq \text{prob(formal)} < 0.8$
block 5: $0.8 \leq \text{prob(formal)} < 1.0$

Table 1.4 – Differences between treatment and control groups

	Probability (Formal)											
	All Sample		block 1		block 2		block 3		block 4		block 5	
	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t
on leave	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.01	0.00
age	-1.38	0.00	0.78	0.13	0.52	0.00	-0.38	0.01	-0.76	0.00	0.06	0.81
white	0.14	0.00	-0.01	0.44	0.04	0.00	0.01	0.22	-0.01	0.23	-0.01	0.18
female	-0.06	0.00	-0.10	0.00	0.04	0.00	-0.02	0.00	-0.01	0.18	0.00	0.74
education	2.33	0.00	0.05	0.51	0.33	0.00	0.03	0.49	0.13	0.00	0.12	0.09
married	0.02	0.00	0.03	0.09	-0.02	0.01	-0.01	0.21	0.01	0.12	0.05	0.00
North	-0.06	0.00	-0.04	0.00	-0.01	0.00	0.00	0.78	0.01	0.01	0.00	0.42
Northeast	-0.11	0.00	0.00	0.89	-0.04	0.00	0.00	0.75	0.01	0.01	0.00	0.89
Southeast	0.10	0.00	0.03	0.00	0.04	0.00	0.00	0.39	-0.01	0.03	0.01	0.58
South	0.08	0.00	0.00	0.99	0.01	0.01	0.01	0.06	0.00	0.86	0.01	0.55
Middle-west	-0.01	0.00	0.01	0.11	0.01	0.09	-0.01	0.11	0.00	0.25	-0.02	0.02
metropolitan area	0.08	0.00	0.10	0.00	0.04	0.00	-0.01	0.05	-0.02	0.01	-0.04	0.00
managers	0.05	0.00	0.00	0.08	0.00	0.00	0.01	0.00	0.00	0.48	-0.02	0.02
scientists and artists	0.03	0.00	-0.01	0.00	0.00	0.93	0.00	0.32	0.01	0.02	-0.01	0.48
techinicians	0.04	0.00	0.00	0.14	0.01	0.00	0.01	0.04	-0.01	0.04	-0.01	0.11
services employees	-0.06	0.00	0.04	0.00	0.04	0.00	-0.02	0.00	-0.04	0.00	-0.02	0.01
salesmans	-0.09	0.00	-0.16	0.00	-0.01	0.08	0.02	0.00	0.00	0.09	0.00	0.37
industry employees	-0.07	0.00	0.12	0.00	-0.04	0.00	-0.02	0.00	0.01	0.22	0.00	0.46
other ocupations	0.00	0.00	(dropped)	0.00	0.00	0.16	0.00	0.01	0.00	0.19	0.00	0.01
administrative services	0.10	0.00	0.00	0.05	0.00	0.53	0.00	0.91	0.03	0.00	0.07	0.00
industrial sector	0.08	0.00	-0.03	0.00	-0.02	0.00	0.00	0.66	0.02	0.00	0.05	0.00
civil construction sector	-0.09	0.00	0.14	0.00	-0.02	0.00	-0.02	0.00	0.00	0.00	0.00	0.76
retail sector	-0.04	0.00	-0.12	0.00	-0.01	0.40	0.01	0.01	-0.02	0.00	0.01	0.50
food and lodging sector	-0.02	0.00	-0.04	0.00	0.01	0.00	0.00	0.60	-0.01	0.00	0.00	0.27
transport communic. sector	0.02	0.00	0.00	0.82	-0.01	0.00	0.00	0.22	0.00	0.21	0.01	0.01
public administration sector	0.03	0.00	0.00	0.32	0.00	0.00	0.01	0.00	0.01	0.00	-0.01	0.15
health and education sector	0.07	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.02	0.00	-0.04	0.00
house-keeping	-0.09	0.00	0.02	0.09	0.02	0.00	-0.03	0.00	0.00	0.07	(dropped)	0.00
other sectors	0.04	0.00	0.02	0.01	0.02	0.00	0.01	0.13	-0.03	0.00	-0.01	0.09

block 1: 0.0 < prob(formal) < 0.2
block 2: 0.2 ≤ prob(formal) < 0.4
block 3: 0.4 ≤ prob(formal) < 0.6
block 4: 0.6 ≤ prob(formal) < 0.8
block 5: 0.8 ≤ prob(formal) < 1.0

Table 1.4a – Differences between treatment and control groups - Female

	Probability (Formal)											
	All Sample		block 1		block 2		block 3		block 4		block 5	
	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t
on leave	0.02	0.00	0.03	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
age	-1.92	0.00	1.21	0.09	0.02	0.92	-0.71	0.00	-0.07	0.79	0.30	0.41
white	0.15	0.00	-0.03	0.17	0.04	0.00	0.00	0.68	-0.02	0.16	-0.01	0.34
education	2.61	0.00	0.03	0.83	0.14	0.03	-0.02	0.79	0.22	0.00	0.14	0.11
married	-0.04	0.00	-0.02	0.48	-0.01	0.55	-0.03	0.00	0.03	0.01	0.02	0.24
North	-0.06	0.00	0.00	0.85	-0.03	0.00	0.02	0.00	0.01	0.04	0.00	0.84
Northeast	-0.11	0.00	-0.04	0.10	-0.03	0.00	0.01	0.21	0.02	0.02	-0.01	0.42
Southeast	0.09	0.00	0.04	0.00	0.05	0.00	-0.05	0.00	-0.01	0.45	-0.01	0.48
South	0.08	0.00	0.00	0.63	0.00	0.59	0.03	0.00	-0.04	0.00	0.02	0.20
Middle-west	0.00	0.46	0.00	0.75	0.00	0.96	-0.01	0.11	0.01	0.06	0.00	0.92
metropolitan area	0.08	0.00	0.13	0.00	0.03	0.00	-0.02	0.09	-0.03	0.03	-0.03	0.14
managers	0.05	0.00	0.00	0.01	0.00	0.89	0.01	0.01	0.02	0.03	-0.03	0.02
scientists and artists	0.05	0.00	-0.01	0.00	-0.01	0.01	0.00	0.45	0.03	0.00	0.00	0.80
techinicias	0.06	0.00	0.00	0.70	0.00	0.16	0.01	0.00	-0.02	0.06	-0.02	0.24
services employees	-0.17	0.00	0.22	0.00	0.01	0.15	-0.06	0.00	-0.05	0.00	-0.02	0.06
salesmans	-0.11	0.00	-0.17	0.00	-0.01	0.13	0.03	0.00	0.00	0.87	(dropped)	0.00
industry employees	-0.04	0.00	-0.04	0.00	0.00	0.65	0.01	0.06	-0.04	0.00	0.00	0.32
other ocupations	0.00	0.16	(dropped)	0.00	(dropped)	0.00	(dropped)	0.00	(dropped)	0.00	(dropped)	0.00
administrative services	0.15	0.00	0.00	0.16	0.00	0.29	0.00	0.33	0.06	0.00	0.07	0.00
industrial sector	-0.01	0.06	-0.05	0.00	0.00	1.00	0.01	0.21	-0.03	0.00	0.02	0.03
civil construction sector	0.00	0.00	0.00	0.62	0.00	0.83	0.00	0.29	0.00	0.87	0.00	0.35
retail sector	-0.02	0.00	-0.15	0.00	-0.02	0.00	0.03	0.00	0.02	0.02	0.02	0.17
food and lodging sector	-0.03	0.00	-0.05	0.00	0.01	0.26	0.00	0.99	0.00	0.38	0.00	0.93
transport communic. sector	0.02	0.00	0.00	0.32	0.00	0.35	0.00	0.08	0.00	0.43	0.02	0.04
public administration sector	0.03	0.00	(dropped)	0.00	0.00	0.04	0.01	0.00	0.02	0.00	-0.02	0.16
health and education sector	0.15	0.00	0.01	0.05	0.01	0.00	0.03	0.00	0.00	0.68	-0.05	0.01
house-keeping	-0.17	0.00	0.20	0.00	0.01	0.56	-0.06	0.00	0.00	0.17	(dropped)	0.00
other sectors	0.03	0.00	0.04	0.00	0.00	0.83	-0.02	0.03	-0.01	0.28	0.01	0.19

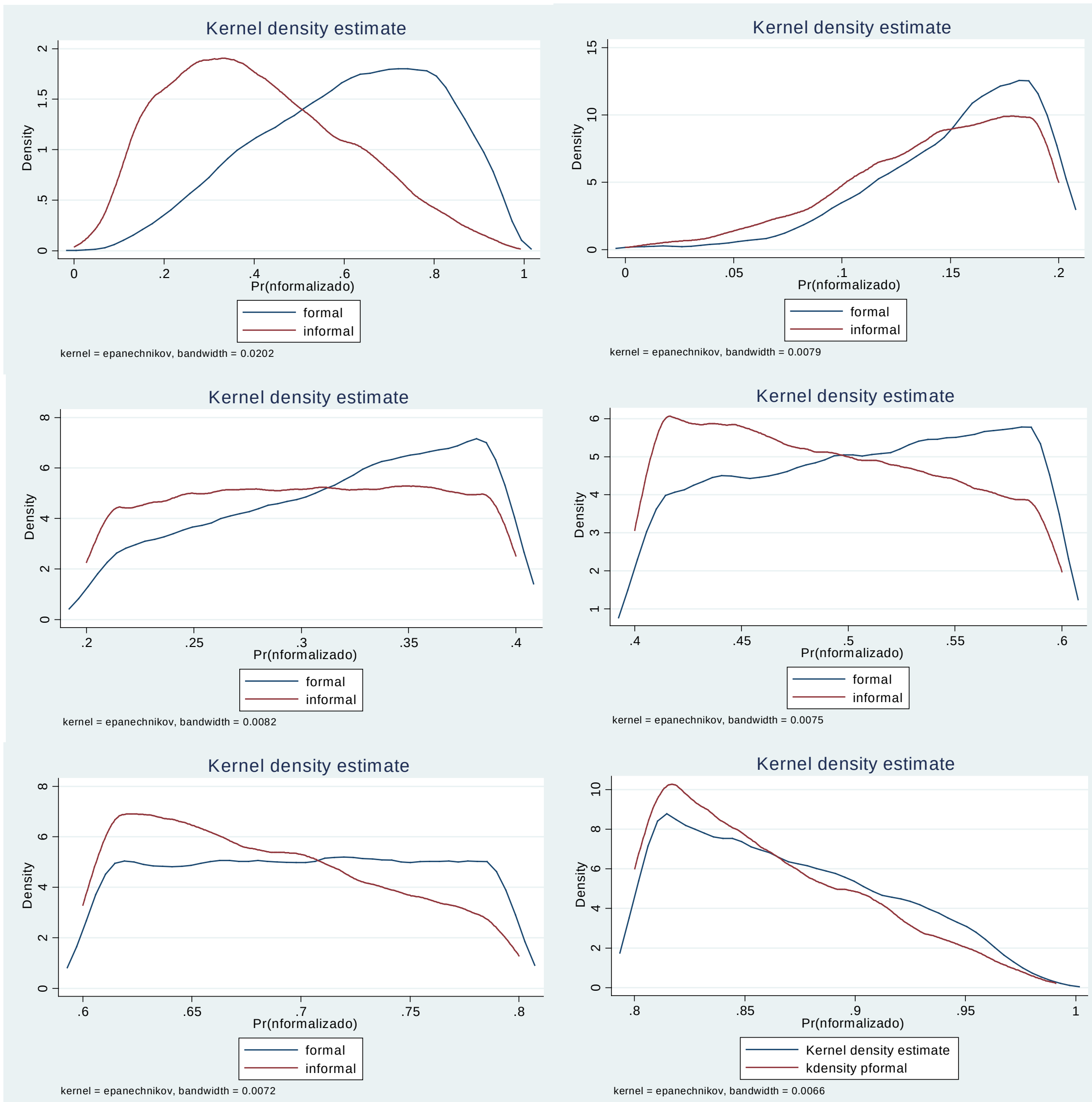
block 1: 0.0 < prob(formal) < 0.2
block 2: 0.2 ≤ prob(formal) < 0.4
block 3: 0.4 ≤ prob(formal) < 0.6
block 4: 0.6 ≤ prob(formal) < 0.8
block 5: 0.8 ≤ prob(formal) < 1.0

Table 1.4b – Differences between treatment and control groups - Male

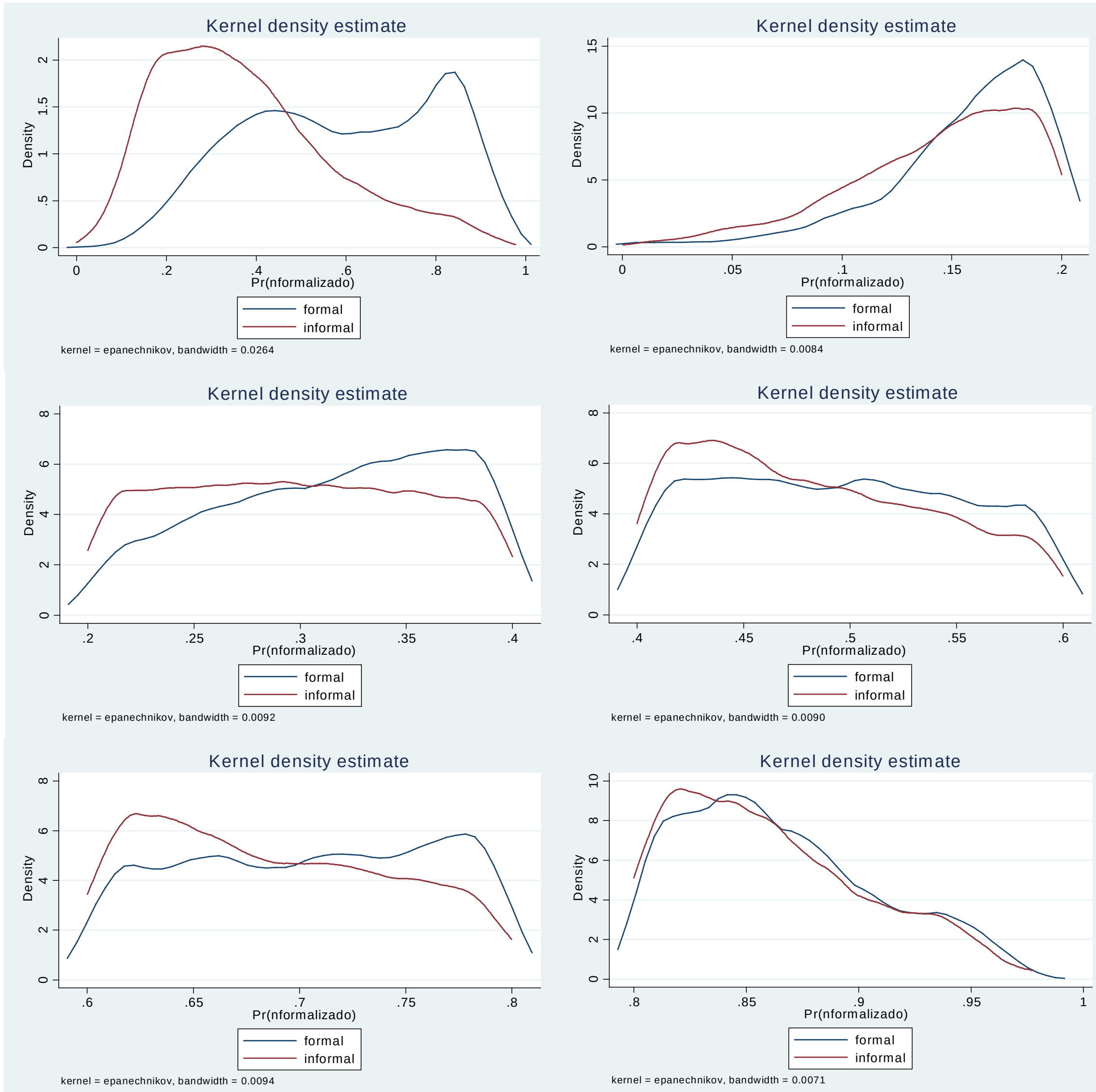
	Probability (Formal)											
	All Sample		block 1		block 2		block 3		block 4		block 5	
	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t	Coef.	P>t
on leave	0.01	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.01	0.00	0.01	0.00
age	-1.05	0.00	-0.01	0.98	0.77	0.00	-0.23	0.23	-0.56	0.00	-0.83	0.01
white	0.13	0.00	-0.02	0.27	0.05	0.00	0.01	0.26	-0.01	0.37	0.00	0.97
education	2.20	0.00	0.14	0.15	0.44	0.00	0.04	0.48	0.06	0.33	0.19	0.04
married	0.05	0.00	0.08	0.00	0.00	0.77	-0.01	0.34	0.00	0.76	0.03	0.04
North	-0.06	0.00	-0.04	0.02	0.00	0.66	-0.01	0.11	0.01	0.19	0.00	0.90
Northeast	-0.12	0.00	0.01	0.56	-0.03	0.00	-0.02	0.01	0.01	0.22	0.00	0.60
Southeast	0.11	0.00	0.02	0.13	0.01	0.28	0.02	0.02	-0.01	0.21	0.02	0.14
South	0.08	0.00	0.00	0.37	0.02	0.01	0.00	0.43	0.01	0.27	0.00	0.89
Middle-west	-0.02	0.00	0.02	0.22	0.00	0.49	0.00	0.45	-0.01	0.05	-0.02	0.01
metropolitan area	0.07	0.00	0.10	0.00	0.04	0.00	0.01	0.20	-0.02	0.02	-0.05	0.00
managers	0.05	0.00	0.01	0.07	0.01	0.00	0.01	0.00	0.00	0.35	-0.03	0.02
scientists and artists	0.02	0.00	0.00	0.23	0.00	0.58	-0.01	0.03	0.01	0.09	0.00	0.79
techinicias	0.02	0.00	0.01	0.05	0.01	0.01	0.00	0.60	-0.01	0.14	0.00	0.96
services employees	0.04	0.00	0.00	0.76	0.02	0.00	0.00	0.89	-0.01	0.16	-0.03	0.02
salesmans	-0.08	0.00	-0.13	0.00	-0.01	0.31	0.02	0.00	-0.01	0.00	0.00	0.41
industry employees	-0.13	0.00	0.11	0.00	-0.04	0.00	-0.02	0.00	0.00	0.61	0.00	0.88
other ocupations	0.00	0.01	(dropped)	0.00	0.00	0.16	0.00	0.01	0.00	0.24	-0.01	0.01
administrative services	0.07	0.00	0.00	0.16	0.00	0.17	0.00	0.78	0.01	0.00	0.07	0.00
industrial sector	0.14	0.00	-0.01	0.00	-0.01	0.01	-0.01	0.13	0.03	0.00	0.05	0.00
civil construction sector	-0.17	0.00	0.13	0.00	-0.02	0.02	-0.03	0.00	0.00	0.01	0.00	1.00
retail sector	-0.06	0.00	-0.09	0.00	0.01	0.32	0.01	0.05	-0.03	0.00	0.00	0.88
food and lodging sector	-0.02	0.00	-0.03	0.00	0.01	0.01	0.00	0.66	-0.01	0.00	0.00	0.00
transport communic. sector	0.01	0.00	-0.01	0.06	-0.02	0.00	0.01	0.28	0.00	0.42	0.02	0.02
public administration sector	0.03	0.00	0.00	0.42	0.00	0.04	0.01	0.00	0.01	0.00	-0.01	0.15
health and education sector	0.03	0.00	0.00	0.13	0.00	0.91	0.00	0.01	0.01	0.01	-0.02	0.02
house-keeping	-0.01	0.00	0.00	0.78	0.01	0.01	0.00	0.79	-0.01	0.00	(dropped)	0.00
other sectors	0.05	0.00	0.01	0.19	0.02	0.00	0.00	0.44	-0.01	0.14	-0.03	0.01

block 1: $0.0 < \text{prob(formal)} < 0.2$
block 2: $0.2 \leq \text{prob(formal)} < 0.4$
block 3: $0.4 \leq \text{prob(formal)} < 0.6$
block 4: $0.6 \leq \text{prob(formal)} < 0.8$
block 5: $0.8 \leq \text{prob(formal)} < 1.0$

Graph 1 - Kernel Density - Prob(formal job) for workers in the formal sector and workers in the informal sector



Graph 1a - Kernel Density - Prob(formal job) for female workers in the formal sector and female workers in the informal sector



Graph 1b - Kernel Density - Prob(formal job) for male workers in the formal sector and male workers in the informal sector

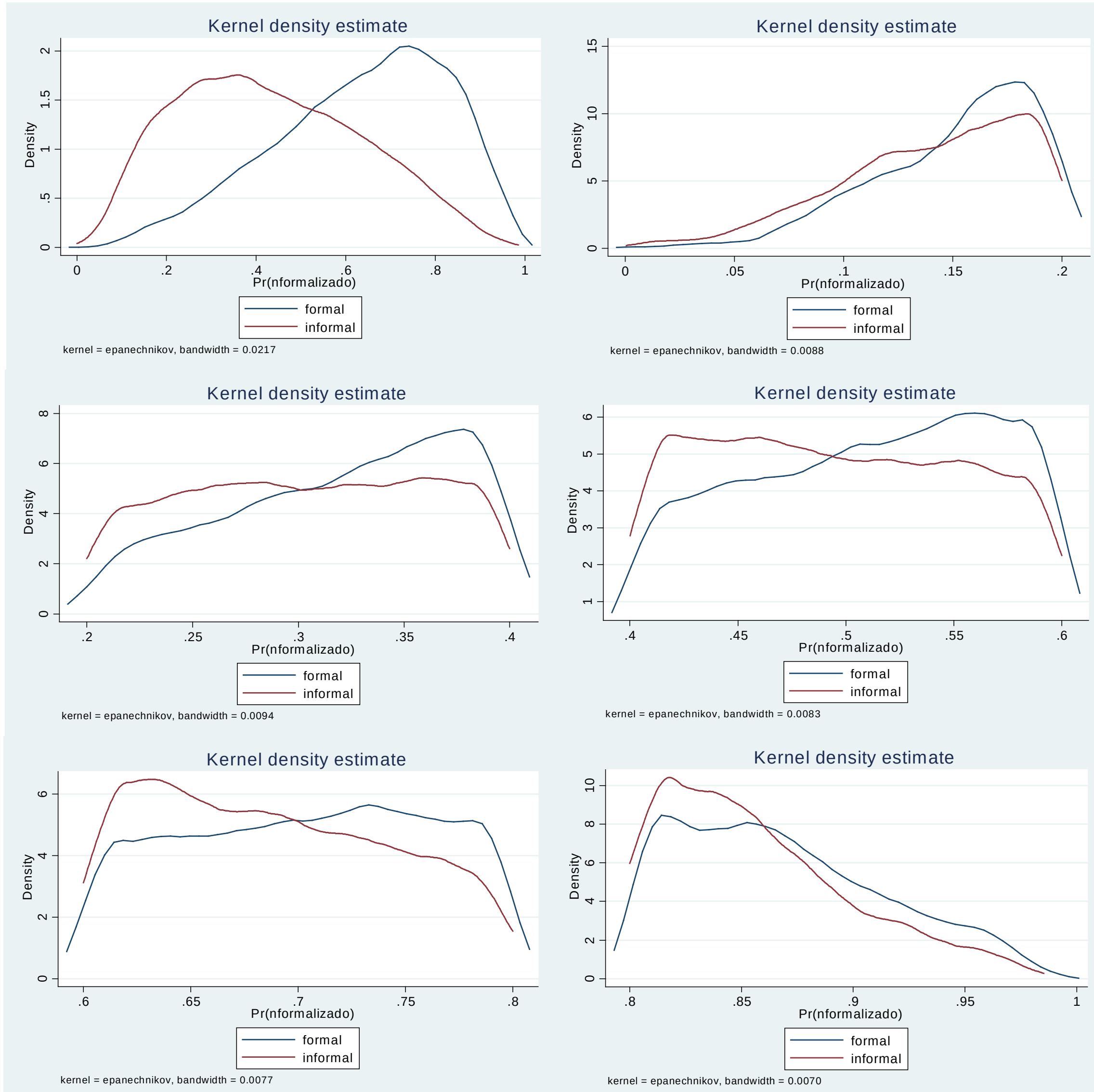


Table 1.5 – Probability to take leave

	all sample	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	0.465	0.435	0.448	0.512	0.449	0.347
	(22.01)***	(5.43)***	(11.21)***	(12.47)***	(8.91)***	(3.63)***
female	0.0852	-0.308	-0.0308	0.153	0.155	0.286
	(4.37)***	(-4.34)***	(-0.77)	(4.13)***	(4.10)***	(5.27)***
good health	0.104	0.261	0.102	0.134	0.0486	0.0886
	(3.71)***	-1.72	-1.5	(2.37)*	-1	-1.4
regular health	0.532	0.537	0.464	0.583	0.582	0.492
	(17.63)***	(3.51)***	(6.66)***	(9.73)***	(10.74)***	(5.90)***
poor health	1.092	0.9	0.965	1.177	1.326	1.442
	(23.42)***	(5.13)***	(10.39)***	(12.84)***	(13.30)***	(7.73)***
really poor health	1.223	0.71	0.816	1.598	1.288	2.107
	(13.61)***	(2.11)*	(4.36)***	(9.98)***	(5.91)***	(6.73)***
_cons	-2.676	-2.515	-2.569	-2.784	-2.675	-2.66
	(-87.16)***	(-17.26)***	(-38.38)***	(-44.98)***	(-43.49)***	(-25.15)***
N	106984	9390	27160	29916	27590	12903

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

block 1: 0.0 < prob(formal) < 0.2
block 2: 0.2 ≤ prob(formal) < 0.4
block 3: 0.4 ≤ prob(formal) < 0.6
block 4: 0.6 ≤ prob(formal) < 0.8
block 5: 0.8 ≤ prob(formal) < 1.0

Table 1.5a – Probability to take leave - Female

	females	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	0.516	0.706	0.499	0.411	0.461	0.381
	(16.66)***	(5.97)***	(9.28)***	(7.01)***	(5.46)***	(2.87)**
good health	0.0762	0.439	0.182	-0.0214	0.0187	0.137
	-1.87	-1.34	-1.89	(-0.28)	-0.24	-1.59
regular health	0.421	0.786	0.402	0.446	0.434	0.479
	(9.50)***	(2.43)*	(4.04)***	(5.46)***	(4.79)***	(4.13)***
poor health	0.862	0.896	0.899	1.006	0.958	1.203
	(11.87)***	(2.49)*	(6.77)***	(7.18)***	(5.12)***	(3.78)***
really poor health	1.171	1.195	1.14	1.285	0.595	2.399
	(9.35)***	(2.60)**	(5.50)***	(4.83)***	-1.15	(5.84)***
_cons	-2.564	-3.055	-2.611	-2.441	-2.454	-2.486
	(-60.44)***	(-9.63)***	(-28.07)***	(-31.92)***	(-25.51)***	(-17.52)***
N	44820	5193	14076	11697	8020	5821

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
block 1: $0.0 < \text{prob(formal)} < 0.2$
block 2: $0.2 \leq \text{prob(formal)} < 0.4$
block 3: $0.4 \leq \text{prob(formal)} < 0.6$
block 4: $0.6 \leq \text{prob(formal)} < 0.8$
block 5: $0.8 \leq \text{prob(formal)} < 1.0$

Table 1.5b – Probability to take leave - Male

	male	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	0.417	0.383	0.457	0.489	0.459	0.409
	(14.47)***	(3.81)***	(7.79)***	(8.69)***	(6.75)***	(3.12)**
good health	0.126	0.196	0.0797	0.13	0.126	0.0512
	(3.26)**	-1.2	-0.81	-1.66	-1.85	-0.6
regular health	0.627	0.412	0.558	0.617	0.669	0.677
	(15.15)***	(2.44)*	(5.57)***	(7.49)***	(8.96)***	(6.74)***
poor health	1.268	0.866	1.118	1.276	1.505	1.479
	(20.60)***	(4.35)***	(8.51)***	(10.49)***	(12.05)***	(7.51)***
really poor health	1.27		0.881	1.509	1.602	1.614
	(9.82)***		(3.24)**	(6.20)***	(6.77)***	(3.32)***
_cons	-2.693	-2.455	-2.63	-2.75	-2.778	-2.698
	(-66.59)***	(-16.03)***	(-28.43)***	(-34.11)***	(-33.14)***	(-19.00)***
N	62164	4856	13461	16908	18126	8771

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
block 1: 0.0 < prob(formal) < 0.2
block 2: 0.2 ≤ prob(formal) < 0.4
block 3: 0.4 ≤ prob(formal) < 0.6
block 4: 0.6 ≤ prob(formal) < 0.8
block 5: 0.8 ≤ prob(formal) < 1.0

Table 1.6 – Average Treatment Effect – Nearest Neighbor Matching Estimator

n. treat.	n. contr.	ATT	Std. Err.	t
55079	26140	0.017	0.001	14.979

Note: the numbers of treated and controls refer to actual nearest neighbour matches

Table 1.7 – Difference in difference estimates

	Prob (on leave)	
	(a)	(b)
Post * Treatment	0.107***	0.107**
	-3.33	-3.24
Post	0.108***	0.115***
	-4.13	-4.3
Treatment	0.274***	0.352***
	-11.03	-13.61
good health		0.0913***
		-4.17
regular health		0.523***
		-22.36
poor health		1.075***
		-30.17
really poor health		1.197***
		-17.63
_cons	-2.447***	-2.740***
	(-121.91)	(-99.45)
N	199750	199750

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1.8 – Oaxaca Blinder Decomposition

"On leave"	Coef.	Std. Err.	P>z
Differential			
Prediction 1998	0.0112	0.0003	0.00
Prediction 2003	0.0176	0.0004	0.00
Difference	-0.0064	0.0005	0.00
Decompasition			
Endowments	-0.0008	0.0003	0.00
Coefficients	-0.0055	0.0006	0.00
Interaction	-0.0001	0.0004	0.86

Chapter 2 Tables and Charts

Table 2.1 – Summary Statistics – Rural Children

	All Sample		Girls		Boys	
	Obs	Mean	Obs	Mean	Obs	Mean
Children between 10 and 14 years old						
Child Labor	12,942	0.36	6,204	0.22	6,738	0.49
Literacy	12,940	0.68	6,204	0.75	6,736	0.61
Attendance	12,942	0.70	6,204	0.73	6,738	0.68
Age	12,942	12.14	6,204	12.13	6,738	12.14
Female	12,942	0.48	6,204	-	6,738	-
White	12,942	0.35	6,204	0.36	6,738	0.34
Education	12,942	1.82	6,204	2.06	6,738	1.61
Family Size	12,942	6.31	6,204	6.32	6,738	6.29
Number of Child in the family	12,942	2.70	6,204	2.72	6,738	2.69
Children between 6 and 14 years old						
Literacy	19,890	0.53	9,627	0.58	10,263	0.49
Attendance	19,898	0.69	9,630	0.71	10,268	0.67
Age	19,898	10.55	9,630	10.52	10,268	10.58
Female	19,898	0.48	9,630	-	10,268	-
White	19,898	0.34	9,630	0.35	10,268	0.33
Education	16,102	1.51	7,760	1.70	8,342	1.34
Family Size	19,898	6.38	9,630	6.39	10,268	6.37
Number of Child in the family	19,898	2.85	9,630	2.86	10,268	2.84

Table 2.1a – Summary Statistics – Rural Children – Socioeconomic Groups

	Obs	Child Labor	Literacy	Attendance	Age	Female	White	Education	Family Size	Number of Child in the family
Children between 10 and 14 years old										
All sample	12,942	0.36	0.68	0.70	12.14	0.48	0.35	1.82	6.31	2.70
SES 1	3,128	0.44	0.53	0.66	12.08	0.47	0.24	1.15	7.85	3.68
SES 2	2,486	0.40	0.60	0.68	12.12	0.47	0.30	1.39	6.14	2.66
SES 3	2,026	0.40	0.66	0.65	12.13	0.46	0.30	1.65	5.82	2.51
SES 4	1,928	0.32	0.83	0.74	12.18	0.48	0.46	2.55	6.16	2.41
SES 5	1,476	0.29	0.94	0.84	12.19	0.50	0.61	3.34	5.49	2.03
Girls	6,204	0.22	0.75	0.73	12.13	1.00	0.36	2.06	6.32	2.72
SES 1	1,481	0.27	0.62	0.70	12.06	1.00	0.25	1.39	7.95	3.80
SES 2	1,162	0.23	0.69	0.73	12.11	1.00	0.30	1.64	6.10	2.63
SES 3	940	0.24	0.74	0.68	12.11	1.00	0.32	1.91	5.84	2.49
SES 4	935	0.20	0.87	0.74	12.21	1.00	0.47	2.76	6.23	2.43
SES 5	741	0.20	0.95	0.84	12.17	1.00	0.62	3.43	5.46	2.02
Boys	6,738	0.49	0.61	0.68	12.14	0.00	0.34	1.61	6.29	2.69
SES 1	1,647	0.60	0.45	0.62	12.10	0.00	0.23	0.93	7.77	3.57
SES 2	1,324	0.55	0.52	0.64	12.13	0.00	0.30	1.16	6.18	2.68
SES 3	1,086	0.54	0.58	0.63	12.15	0.00	0.29	1.42	5.81	2.53
SES 4	993	0.44	0.79	0.75	12.15	0.00	0.46	2.35	6.09	2.38
SES 5	735	0.39	0.93	0.84	12.21	0.00	0.60	3.24	5.53	2.04
Children between 6 and 14 years old										
All sample	19,890		0.53	0.69	10.55	0.48	0.34	1.51	6.38	2.85
SES 1	4,962		0.39	0.63	10.43	0.48	0.24	0.95	7.95	3.86
SES 2	3,182		0.46	0.66	10.54	0.47	0.29	1.11	6.17	2.78
SES 3	3,102		0.51	0.64	10.56	0.47	0.29	1.36	5.89	2.66
SES 4	2,907		0.69	0.75	10.64	0.48	0.45	2.14	6.21	2.54
SES 5	2,200		0.82	0.84	10.68	0.50	0.60	2.86	5.52	2.14
Girls	9,630		0.58	0.71	10.52	1.00	0.35	1.70	6.39	2.86
SES 1	2,404		0.44	0.66	10.35	1.00	0.25	1.15	8.00	3.94
SES 2	1,811		0.52	0.68	10.50	1.00	0.29	1.29	6.15	2.77
SES 3	1,454		0.58	0.66	10.51	1.00	0.30	1.57	5.87	2.62
SES 4	1,399		0.72	0.75	10.69	1.00	0.45	2.32	6.27	2.56
SES 5	1,094		0.83	0.84	10.70	1.00	0.61	2.96	5.51	2.13
Boys	10,268		0.49	0.67	10.58	0.00	0.33	1.34	6.37	2.84
SES 1	2,558		0.33	0.59	10.50	0.00	0.23	0.77	7.91	3.79
SES 2	2,006		0.40	0.64	10.59	0.00	0.29	0.94	6.20	2.79
SES 3	1,648		0.46	0.62	10.60	0.00	0.28	1.17	5.92	2.70
SES 4	1,508		0.66	0.75	10.58	0.00	0.45	1.97	6.16	2.53
SES 5	1,107		0.81	0.84	10.66	0.00	0.60	2.77	5.54	2.14

Obs: SES stands for socioeconomic index

Table 2.2 – Family Income Regression

Outcome *Log Per Capita Family Income*	All Sample	Socioeconomic Index Quintile (I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	-0.0596	0.0678	0.0311	-0.0513	-0.0236	-0.0312
	(0.00982)***	(0.0279)*	-0.0237	(0.0240)*	-0.0277	-0.03
Male Treatment old rule	-0.026	-0.0593	0.0749	0.012	0.0871	0.0178
	(0.00958)**	(0.0265)*	(0.0228)**	-0.0235	(0.0269)**	-0.0306
Female Treatment new rule	-0.047	-0.0155	-0.0222	-0.0485	-0.141	-0.0647
	(0.00753)***	-0.0211	-0.0161	(0.0170)**	(0.0193)***	(0.0213)**
Male Treatment new rule	-0.0262	0.0258	0.00243	-0.103	-0.0395	-0.00674
	(0.00961)**	-0.0235	-0.02	(0.0209)***	-0.0233	-0.0271
Post	-0.107	-0.149	-0.0892	-0.125	-0.185	-0.194
	(0.00761)***	(0.0165)***	(0.0171)***	(0.0184)***	(0.0186)***	(0.0194)***
Female Treatment old rule x *Post (a)*	0.332	0.268	0.206	0.291	0.278	0.224
	(0.0112)***	(0.0294)***	(0.0290)***	(0.0287)***	(0.0310)***	(0.0313)***
Male Treatment old rule x *Post (b)*	0.296	0.39	0.225	0.265	0.135	0.146
	(0.0105)***	(0.0266)***	(0.0251)***	(0.0259)***	(0.0283)***	(0.0316)***
Female Treatment new rule x *Post (c)*	0.162	0.125	0.144	0.0779	0.244	0.191
	(0.0104)***	(0.0264)***	(0.0240)***	(0.0248)**	(0.0262)***	(0.0275)***
Male Treatment new rule x *Post (d)*	0.147	0.264	0.0918	0.2	0.111	0.0217
	(0.0129)***	(0.0288)***	(0.0289)**	(0.0297)***	(0.0313)***	-0.0334
N	114900	17891	18197	18018	18229	18371

standard errors in parentheses

* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.3 – Child Labor – Socio Economic Index

Outcome *Child Labor*	All Sample	Socioeconomic Index Quintile (I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	0.00586	0.0976	-0.0119	0.0304	-0.00847	-0.0224
	-0.0195	(0.0482)*	-0.054	-0.0508	-0.05	-0.0573
Male Treatment old rule	-0.00166	0.11	0.0218	-0.0872	-0.0521	0.0319
	-0.018	(0.0425)**	-0.0437	-0.0461	-0.0473	-0.0594
Female Treatment new rule	0.0391	0.0867	-0.0357	0.122	0.0429	0.0758
	(0.0139)**	(0.0369)*	-0.029	(0.0347)***	-0.036	-0.0415
Male Treatment new rule	-0.00837	0.00512	-0.00655	-0.0456	-0.0652	0.0225
	-0.0163	-0.0368	-0.0348	-0.0395	-0.0377	-0.0516
Post	0.105	0.11	0.0876	0.0853	0.13	0.139
	(0.0117)***	(0.0238)***	(0.0264)***	(0.0300)**	(0.0298)***	(0.0322)***
Female Treatment old rule x *Post (a)*	-0.0038	-0.0112	-0.0863	0.00269	0.0128	0.0771
	-0.0217	-0.0477	-0.0625	-0.0585	-0.0568	-0.0578
Male Treatment old rule x *Post (b)*	0.00123	-0.013	0.0606	0.0304	-0.00846	0.0508
	-0.0196	-0.0436	-0.0477	-0.0508	-0.0519	-0.0653
Female Treatment new rule x *Post (c)*	-0.0479	-0.121	-0.00403	-0.0308	-0.069	-0.0789
	(0.0196)*	(0.0469)**	-0.0457	-0.0496	-0.0495	-0.0572
Male Treatment new rule x *Post (d)*	-0.00377	0.0114	0.0519	-0.0397	0.0446	-0.025
	-0.0222	-0.0449	-0.0524	-0.0544	-0.0536	-0.0653
N	12940	3128	2486	2026	1927	1476

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.3a – Child Labor – Girls – Socioeconomic Index

Outcome *Child Labor - Girls*	All Sample	Socioeconomic Index Quintile				
		(I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	0.000667	0.0948	-0.052	0.0747	-0.0659	0.014
	-0.0251	-0.0666	-0.0798	-0.0645	-0.0578	-0.0737
Male Treatment old rule	-0.0454	0.0795	-0.0802	-0.119	-0.115	-0.0317
	(0.0229)*	-0.0569	-0.0594	-0.0617	(0.0566)*	-0.0693
Female Treatment new rule	0.0232	0.112	-0.072	0.114	-0.0205	0.0402
	-0.0175	(0.0506)*	(0.0354)*	(0.0494)*	-0.0458	-0.0499
Male Treatment new rule	-0.034	0.00122	-0.0661	-0.0722	-0.0524	-0.0165
	-0.0202	-0.0484	-0.0436	-0.051	-0.0434	-0.0649
Post	0.0997	0.146	0.0625	0.0627	0.119	0.0794
	(0.0155)***	(0.0332)***	-0.0365	-0.0401	(0.0386)**	-0.0421
Female Treatment old rule x *Post (a)*	-0.0148	-0.0377	-0.126	-0.00977	0.0417	0.0842
	-0.0281	-0.0643	-0.0886	-0.077	-0.0702	-0.0749
Male Treatment old rule x *Post (b)*	0.0223	0.00758	0.208	0.0192	-0.0281	0.0371
	-0.0253	-0.0593	(0.0657)**	-0.0683	-0.0627	-0.0768
Female Treatment new rule x *Post (c)*	-0.0431	-0.17	-0.0622	0.00152	-0.0224	0.0169
	-0.0257	(0.0648)**	-0.0605	-0.0721	-0.0632	-0.0745
Male Treatment new rule x *Post (d)*	0.00342	-0.0026	0.0985	0.0234	-0.0127	0.00977
	-0.0287	-0.0609	-0.0704	-0.0732	-0.0652	-0.0841
N	6202	1481	1162	940	934	741

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.3b – Child Labor – Boys – Socioeconomic Index

Outcome *Child Labor - Boys*	All Sample	Socioeconomic Index Quintile				
		(I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	0.00475	0.0929	0.0244	-0.0357	0.026	-0.0542
	-0.0296	-0.0686	-0.0737	-0.0766	-0.0804	-0.0894
Male Treatment old rule	0.0392	0.135	0.108	-0.0672	-0.00835	0.127
	-0.0273	(0.0628)*	-0.0641	-0.0661	-0.0722	-0.104
Female Treatment new rule	0.0543	0.0624	0.00298	0.119	0.106	0.114
	(0.0212)*	-0.0532	-0.045	(0.0483)*	-0.0556	-0.0691
Male Treatment new rule	0.0165	0.015	0.0306	-0.0151	-0.0715	0.0789
	-0.0253	-0.0544	-0.0539	-0.0606	-0.0597	-0.081
Post	0.111	0.0783	0.109	0.0916	0.137	0.221
	(0.0171)***	(0.0338)*	(0.0377)**	(0.0439)*	(0.0444)**	(0.0491)***
Female Treatment old rule x *Post (a)*	0.00764	0.00258	-0.0551	0.046	0.00709	0.05
	-0.033	-0.07	-0.0869	-0.0874	-0.0915	-0.0908
Male Treatment old rule x *Post (b)*	-0.0176	-0.0209	-0.0617	0.0573	0.0123	0.0301
	-0.0294	-0.0636	-0.0675	-0.0719	-0.0785	-0.113
Female Treatment new rule x *Post (c)*	-0.0557	-0.0831	0.0239	-0.0557	-0.118	-0.182
	-0.0291	-0.0671	-0.067	-0.0681	-0.0765	(0.0888)*
Male Treatment new rule x *Post (d)*	-0.0131	0.0249	0.0172	-0.087	0.0931	-0.0987
	-0.0333	-0.065	-0.0776	-0.0802	-0.0849	-0.0999
N	6738	1647	1324	1086	993	735

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.4 – Literacy – Socioeconomic Index

Outcome *Literacy*	All Sample	Socioeconomic Index Quintile (I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	-0.0242	0.00209	-0.0722	0.0119	-0.0213	0.0602
	-0.0146	-0.0333	(0.0360)*	-0.0391	-0.036	-0.0332
Male Treatment old rule	-0.0445	-0.0186	-0.0772	-0.0271	-0.0832	-0.00905
	(0.0136)**	-0.0306	(0.0316)*	-0.036	(0.0343)*	-0.0404
Female Treatment new rule	-0.0363	0.00892	-0.0777	0.0135	-0.0741	-0.0335
	(0.0110)***	-0.0277	(0.0229)***	-0.026	(0.0289)*	-0.0286
Male Treatment new rule	-0.036	-0.0359	-0.0389	-0.0615	-0.0532	0.0362
	(0.0130)**	-0.027	-0.0285	(0.0307)*	-0.029	-0.0363
Post	0.0225	0.0662	0.0136	0.0381	0.00485	0.0265
	(0.00901)*	(0.0178)***	-0.0211	-0.0234	-0.0215	-0.02
Female Treatment old rule x *Post (a)*	0.0106	0.0123	0.0509	-0.0581	0.00603	-0.0473
	-0.016	-0.0343	-0.0447	-0.0438	-0.0388	-0.0329
Male Treatment old rule x *Post (b)*	0.0264	0.0041	0.014	0.0662	0.00156	0.004
	-0.0148	-0.0315	-0.0351	-0.0396	-0.0389	-0.0432
Female Treatment new rule x *Post (c)*	0.0232	-0.0193	0.0706	-0.0476	0.0594	-0.00603
	-0.0151	-0.0352	(0.0358)*	-0.0375	-0.0376	-0.0363
Male Treatment new rule x *Post (d)*	0.0503	0.0919	0.0232	0.0506	0.0262	0.00874
	(0.0172)**	(0.0332)**	-0.0413	-0.0425	-0.04	-0.0427
	19887	4962	3813	3100	2905	2200

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.4a – Literacy – Girls – Socioeconomic Index

Outcome	All Sample	Socioeconomic Index Quintile				
Literacy - Girls		(I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	-0.0286	0.0277	-0.0644	-0.0117	-0.0388	0.0287
	-0.0202	-0.0494	-0.0506	-0.0556	-0.05	-0.0478
Male Treatment old rule	-0.0498	0.031	-0.0597	-0.0648	-0.0821	-0.0233
	(0.0190)**	-0.044	-0.0441	-0.0519	-0.0501	-0.0522
Female Treatment new rule	-0.0326	0.021	-0.0691	-0.0133	-0.0673	-0.0427
	(0.0152)*	-0.0372	(0.0330)*	-0.0378	-0.0393	-0.0392
Male Treatment new rule	-0.0294	0.000462	0.0151	-0.105	-0.0456	0.0342
	-0.0184	-0.0411	-0.0408	(0.0426)*	-0.0419	-0.0511
Post	0.031	0.0758	0.0201	0.0394	0.0291	0.0326
	(0.0125)*	(0.0252)**	-0.0301	-0.0323	-0.0296	-0.0284
Female Treatment old rule x *Post (a)*	0.0141	0.0362	0.0529	-0.0995	0.021	-0.0253
	-0.0219	-0.0492	-0.0631	-0.0607	-0.0519	-0.0444
Male Treatment old rule x *Post (b)*	0.0231	-0.0155	-0.00325	0.0435	0.00534	0.0174
	-0.0207	-0.0448	-0.0511	-0.0573	-0.0558	-0.0562
Female Treatment new rule x *Post (c)*	0.0165	-0.0314	0.0832	-0.0411	0.0639	-0.0128
	-0.021	-0.048	-0.052	-0.0537	-0.0497	-0.051
Male Treatment new rule x *Post (d)*	0.0627	0.0953	-0.0128	0.0739	0.0399	0.0352
	(0.0241)**	-0.0491	-0.059	-0.0612	-0.0551	-0.0568
N	9625	2404	1810	1453	1398	1094

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.4b – Literacy – Boys – Socioeconomic Index

Outcome *Literacy - Boys*	All Sample	Socioeconomic Index Quintile (I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	-0.0204	-0.023	-0.0704	0.0217	-0.000939	0.0767
	-0.0209	-0.0447	-0.0508	-0.0554	-0.0524	-0.0469
Male Treatment old rule	-0.0404	-0.0661	-0.0893	0.00467	-0.0907	-0.0131
	(0.0193)*	-0.0428	(0.0452)*	-0.0499	-0.0478	-0.0638
Female Treatment new rule	-0.0398	-0.00484	-0.0867	0.0348	-0.0813	-0.0286
	(0.0156)*	-0.04	(0.0317)**	-0.0358	-0.0425	-0.0414
Male Treatment new rule	-0.0447	-0.0697	-0.0856	-0.0198	-0.0651	0.0319
	(0.0183)*	-0.0357	(0.0396)*	-0.0439	-0.0404	-0.0515
Post	0.014	0.0606	0.00925	0.0326	-0.0139	0.0137
	-0.0129	(0.0250)*	-0.0294	-0.0337	-0.031	-0.0282
Female Treatment old rule x *Post (a)*	0.00674	-0.0134	0.0545	-0.00548	-0.0249	-0.0606
	-0.0233	-0.0477	-0.0625	-0.0638	-0.058	-0.0502
Male Treatment old rule x *Post (b)*	0.0292	0.0194	0.0101	0.0931	0.0016	0.00666
	-0.0209	-0.044	-0.0487	-0.0548	-0.0546	-0.0667
Female Treatment new rule x *Post (c)*	0.0308	-0.00593	0.0694	-0.0571	0.0497	0.00761
	-0.0215	-0.0506	-0.0493	-0.0526	-0.0563	-0.0519
Male Treatment new rule x *Post (d)*	0.0401	0.0825	0.0544	0.0322	0.0103	-0.00635
	-0.0244	-0.0451	-0.0577	-0.0593	-0.0584	-0.0628
N	10262	2558	2003	1647	1507	1106

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.5 – Attendance – Socioeconomic Index

Outcome *Attendance*	All Sample	Socioeconomic Index Quintile				
		(I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	0.00414	0.00733	0.0705	0.0487	0.0152	-0.0389
	-0.0156	-0.0372	-0.0394	-0.0414	-0.039	-0.0426
Male Treatment old rule	0.00394	-0.0378	0.0575	0.0164	0.0747	-0.0831
	-0.0147	-0.035	-0.034	-0.0393	(0.0353)*	-0.0462
Female Treatment new rule	-0.0112	-0.00553	-0.0124	0.0141	-0.0501	-0.0206
	-0.0119	-0.0312	-0.0257	-0.0288	-0.0326	-0.031
Male Treatment new rule	-0.026	-0.0864	0.00369	-0.0153	-0.00933	0.00609
	-0.0141	(0.0312)**	-0.0298	-0.0341	-0.0336	-0.0362
Post	0.0462	0.0332	0.0554	0.073	0.0382	0.0451
	(0.00952)***	-0.0196	(0.0217)*	(0.0252)**	-0.023	-0.023
Female Treatment old rule x *Post (a)*	0.0283	0.0274	0.0263	0.0267	0.0287	0.0229
	-0.0167	-0.0377	-0.0452	-0.045	-0.0407	-0.0402
Male Treatment old rule x *Post (b)*	0.0378	0.109	0.0282	-0.0163	-0.0235	0.0856
	(0.0156)*	(0.0353)**	-0.0368	-0.0432	-0.0384	-0.0469
Female Treatment new rule x *Post (c)*	-0.0000367	0.009	0.0176	-0.0543	0.0512	-0.0404
	-0.0162	-0.0389	-0.038	-0.0412	-0.041	-0.0399
Male Treatment new rule x *Post (d)*	0.0488	0.119	0.0142	0.0152	0.0491	0.0143
	(0.0183)**	(0.0373)**	-0.0428	-0.0461	-0.0434	-0.0436
N	19895	4963	3817	3102	2905	2201

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.5a – Attendance – Girls – Socioeconomic Index

Outcome *Attendance - Girls*	All Sample	Socioeconomic Index Quintile				
		(I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	-0.0265	-0.0321	0.06	0.0516	-0.0107	-0.104
	-0.0219	-0.0521	-0.0564	-0.0568	-0.0573	-0.0622
Male Treatment old rule	-0.00406	-0.0392	0.082	0.0123	0.0479	-0.0952
	-0.0211	-0.0487	-0.0482	-0.0595	-0.055	-0.0651
Female Treatment new rule	0.00729	-0.014	0.0234	0.0329	-0.0272	-0.0608
	-0.0169	-0.044	-0.0361	-0.0433	-0.0455	-0.0444
Male Treatment new rule	-0.0148	-0.0496	0.00408	0.00338	-0.0138	0.0305
	-0.0201	-0.045	-0.0427	-0.0479	-0.0495	-0.0513
Post	0.0421	0.00881	0.0721	0.0976	0.0232	0.0388
	(0.0136)**	-0.0279	(0.0313)*	(0.0364)**	-0.0331	-0.0318
Female Treatment old rule x *Post (a)*	0.0646	0.112	0.0325	0.039	0.0759	0.0667
	(0.0231)**	(0.0527)*	-0.0632	-0.0611	-0.0572	-0.0578
Male Treatment old rule x *Post (b)*	0.0517	0.111	0.0088	0.00406	0.0299	0.108
	(0.0220)*	(0.0492)*	-0.0519	-0.0629	-0.0557	-0.0644
Female Treatment new rule x *Post (c)*	0.00928	0.0582	0.0348	-0.0176	0.0229	-0.0379
	-0.0226	-0.0544	-0.0526	-0.0591	-0.0574	-0.0584
Male Treatment new rule x *Post (d)*	0.0437	0.0949	0.0334	-0.0192	0.0676	-0.0147
	-0.0258	-0.0534	-0.0604	-0.0661	-0.062	-0.062
N	9628	2405	1811	1454	1398	1094

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Table 2.5b – Attendance – Boys – Socioeconomic Index

Outcome *Attendance - Boys*	All Sample	Socioeconomic Index Quintile				
		(I)	(II)	(III)	(IV)	(V)
Female Treatment old rule	0.0325	0.0458	0.0885	0.0487	0.0437	0.00969
	-0.0223	-0.0531	-0.055	-0.06	-0.0535	-0.0578
Male Treatment old rule	0.00986	-0.0357	0.0351	0.0189	0.0967	-0.0778
	-0.0205	-0.0504	-0.0484	-0.0523	(0.0461)*	-0.0656
Female Treatment new rule	-0.0288	0.00367	-0.0461	-0.000932	-0.0731	0.0137
	-0.0169	-0.0445	-0.0366	-0.0389	-0.0466	-0.0433
Male Treatment new rule	-0.0389	-0.12	0.00446	-0.0285	-0.00537	-0.0139
	-0.0198	(0.0433)**	-0.0416	-0.0488	-0.0457	-0.0511
Post	0.0484	0.0567	0.0419	0.0487	0.0543	0.0478
	(0.0133)***	(0.0276)*	-0.0299	-0.0353	-0.0319	-0.0335
Female Treatment old rule x *Post (a)*	-0.00648	-0.0581	0.023	0.013	-0.0232	-0.000429
	-0.0242	-0.0543	-0.0648	-0.0662	-0.0583	-0.0554
Male Treatment old rule x *Post (b)*	0.0262	0.11	0.0316	-0.0253	-0.0683	0.0672
	-0.0221	(0.0507)*	-0.0519	-0.0597	-0.0535	-0.0686
Female Treatment new rule x *Post (c)*	-0.00622	-0.0399	0.0095	-0.0833	0.082	-0.0304
	-0.023	-0.0557	-0.0544	-0.0576	-0.0591	-0.055
Male Treatment new rule x *Post (d)*	0.0555	0.14	-0.00546	0.0456	0.0336	0.0378
	(0.0259)*	(0.0522)**	-0.0605	-0.0645	-0.0612	-0.062
N	10267	2558	2006	1648	1507	1107

standard errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Obs: control variables are household head's education, gender, race, age and age squared; oldest member's education and age; dummy for head-oldest member; age; age squared; race; gender; family size; number of children.

Chapter 3 Tables and Charts

Table 3.1 – Summary Statistics

	2008			2009		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Portuguese Proficiency	11,011	145.76	42.92	10,892	169.79	46.75
Mathematics Proficiency	10,245	159.56	45.52	10,913	177.07	46.65
Lagged Portuguese Proficiency	11,033	123.92	40.34	11,011	145.76	42.92
Lagged Mathematics Proficiency	10,995	129.95	44.66	10,245	159.56	45.52
Father´s Education	9,435	4.18	2.04	10,622	4.30	2.10
Age	11,418	9.56	0.79	11,418	10.56	0.79
Female	11,418	0.46	0.50	11,418	0.46	0.50
White	11,418	0.40	0.49	11,418	0.40	0.49

Table 3.2 – Delta Proficiency Level

	2008	2009	average increment
All sample			
mathematics	28.17	18.93	23.56
portuguese	22.12	23.57	22.84
Low Achievement Students			
mathematics	49.19	38.41	43.67
portuguese	39.49	35.46	37.51
High Achievement Students			
mathematics	10.47	6.87	8.70
portuguese	8.66	15.18	11.92
Medium Achievement Students			
mathematics	27.63	15.53	21.63
portuguese	20.27	22.07	21.17
First Quartile of Class Distribution			
mathematics	43.40	32.08	37.56
portuguese	35.33	32.42	33.86
Second Quartile of Class Distribution			
mathematics	32.26	18.18	25.34
portuguese	26.12	24.42	25.28
Third Quartile of Class Distribution			
mathematics	21.81	13.22	17.50
portuguese	15.30	19.37	17.33
Fourth Quartile of Class Distribution			
mathematics	8.80	4.79	6.90
portuguese	5.89	13.35	9.50

Table 3.3 – Teacher Impact on Student Achievement

	Portuguese				Mathematics			
	(I)		(II)		(III)		(IV)	
	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t
Lagged proficiency	0.570	0.000	0.569	0.000	0.550	0.000	0.550	0.000
Year 2009 dummy	-0.115	0.165	-0.149	0.084	0.353	0.000	0.325	0.001
Age	0.001	0.957	0.001	0.939	0.008	0.574	0.008	0.576
Father's education	0.031	0.000	0.031	0.000	0.027	0.000	0.027	0.000
Female	0.087	0.000	0.086	0.000	-0.025	0.186	-0.027	0.159
White	0.048	0.005	0.045	0.009	0.050	0.012	0.050	0.011
Class size	0.009	0.114	0.010	0.083	-0.011	0.091	-0.009	0.168
Peer's gender			0.139	0.469			0.228	0.300
Peer's race			0.424	0.038			-0.055	0.814
σj	0.39		0.38		0.42		0.42	
Variance	0.15		0.14		0.17		0.17	

Table 3.4 – Teacher Impact on Low and High Ability Students

	Portuguese						Mathematics					
	Low Achievement		Medium Achievement		High Achievement		Low Achievement		Medium Achievement		High Achievement	
	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t
Lagged proficiency	0.265	0.000	0.599	0.000	0.644	0.000	0.194	0.000	0.662	0.000	0.426	0.000
Year dummy	-0.562	0.001	-0.027	0.828	0.084	0.740	0.087	0.673	0.226	0.133	0.409	0.094
Age	0.029	0.214	0.012	0.546	-0.036	0.176	-0.023	0.492	0.035	0.128	0.024	0.422
Father's education	0.017	0.037	0.021	0.001	0.031	0.001	0.020	0.064	0.024	0.001	0.029	0.006
Female	0.067	0.041	0.057	0.017	0.089	0.022	0.007	0.865	-0.045	0.102	0.046	0.282
White	0.009	0.798	0.078	0.002	-0.003	0.947	0.002	0.954	0.049	0.086	0.012	0.788
Class size	0.030	0.034	0.007	0.415	0.006	0.658	0.013	0.480	-0.006	0.579	-0.015	0.283
Peer's gender	1.454	0.005	-0.367	0.146	0.463	0.382	0.079	0.876	-0.042	0.900	0.804	0.150
Peer's race	-0.489	0.441	0.334	0.235	0.887	0.070	-0.940	0.112	0.071	0.846	-0.140	0.779
σ_j	0.61		0.48		0.57		0.60		0.51		0.73	
Variance	0.37		0.23		0.33		0.36		0.26		0.53	

Table 3.5 – Teacher Impact on Different Students inside the Classroom

	Portuguese							
	(I)		(II)		(III)		(IV)	
	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t
Lagged proficiency	0.443	0.000	0.627	0.000	0.709	0.000	0.492	0.000
Year dummy	-0.179	0.264	-0.482	0.005	-0.232	0.164	0.280	0.161
Age	0.009	0.748	0.037	0.225	-0.013	0.667	-0.011	0.704
Father's education	0.029	0.002	0.012	0.222	0.033	0.000	0.023	0.036
Female	0.060	0.107	0.063	0.094	0.039	0.285	0.084	0.054
White	0.023	0.550	0.129	0.001	0.026	0.484	0.003	0.948
Class size	-0.003	0.784	0.020	0.072	0.018	0.095	0.008	0.575
Peer's gender	0.476	0.172	0.043	0.912	0.392	0.280	-0.429	0.370
Peer's race	-0.200	0.582	0.602	0.128	0.564	0.167	0.680	0.222
σ_j	0.509		0.515		0.516		0.658	
Variance	0.259		0.265		0.266		0.434	
Chow's Test*	1.36		0.86		0.90		1.34	

	Mathematics							
	(I)		(II)		(III)		(IV)	
	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t	Coefficient	P>t
Lagged proficiency	0.439	0.000	0.669	0.000	0.648	0.000	0.343	0.000
Year dummy	0.424	0.023	0.089	0.663	0.262	0.174	0.400	0.088
Age	-0.040	0.240	-0.029	0.456	0.041	0.244	-0.002	0.947
Father's education	0.035	0.001	0.009	0.414	0.032	0.002	0.032	0.018
Female	0.044	0.263	-0.020	0.649	-0.066	0.120	-0.073	0.167
White	-0.001	0.979	0.073	0.126	0.076	0.080	0.039	0.448
Class size	-0.020	0.091	0.001	0.920	0.001	0.950	-0.008	0.633
Peer's gender	0.298	0.401	0.111	0.813	0.635	0.136	-0.071	0.911
Peer's race	-0.388	0.311	-0.304	0.543	-0.021	0.964	1.107	0.072
σ_j	0.543		0.582		0.576		0.779	
Variance	0.295		0.339		0.332		0.607	
Chow's Test*	1.34		0.92		1.02		1.50	

* Chow´s test compares the parameters of the especific category of students with the rest of the students in the sample

APPENDIX

Appendix Chapter 1

Table 1.A1 – Probability to "quit doing some activity for health reasons" - Females

	female	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	-0.00215	-0.105	-0.019	-0.0016	-0.0148	-0.0322
	(-0.11)	(-1.18)	(-0.54)	(-0.04)	(-0.30)	(-0.39)
good health	0.284	0.418	0.373	0.304	0.19	0.263
	(8.81)***	(2.87)**	(5.36)***	(4.74)***	(3.04)**	(3.52)***
regular health	1.012	1.157	1.092	1.059	0.876	1.028
	(30.67)***	(8.09)***	(15.77)***	(16.04)***	(12.70)***	(11.42)***
poor health	1.721	1.748	1.844	1.892	1.482	1.859
	(34.50)***	(11.02)***	(20.55)***	(17.43)***	(10.06)***	(6.88)***
really poor health	1.887	2.007	1.872	2.066	1.863	2.278
	(20.25)***	(8.95)***	(12.70)***	(9.53)***	(5.49)***	(5.62)***
_cons	-2.011	-2.173	-2.076	-2.065	-1.852	-1.996
	(-64.90)***	(-15.68)***	(-31.50)***	(-33.76)***	(-28.78)***	(-21.35)***
N	44818	5193	14075	11697	8019	5821

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1.A2 – Probability to "quit doing some activity for health reasons" - Males

	males	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	0.0248	0.0263	-0.013	0.0417	0.0528	0.0252
	-1.34	-0.32	(-0.31)	-1.17	-1.36	-0.34
good health	0.279	0.408	0.31	0.234	0.267	0.311
	(9.38)***	(2.85)**	(4.17)***	(4.03)***	(5.24)***	(4.47)***
regular health	1.032	1.144	1.099	0.99	0.989	1.03
	(33.43)***	(8.07)***	(14.76)***	(16.61)***	(17.95)***	(12.78)***
poor health	1.693	1.746	1.672	1.735	1.743	1.653
	(35.77)***	(10.90)***	(17.02)***	(18.93)***	(16.64)***	(9.41)***
really poor health	1.851	1.994	1.868	1.774	1.89	1.862
	(18.95)***	(7.24)***	(10.66)***	(8.99)***	(9.20)***	(4.09)***
_cons	-2.185	-2.268	-2.209	-2.179	-2.18	-2.206
	(-75.48)***	(-16.76)***	(-31.75)***	(-39.25)***	(-40.71)***	(-25.13)***
N	62160	4883	13461	16908	18124	8770

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1.A3 – Probability to be "on leave" and "quit doing some activity for health reasons" - Females

	females	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	0.551	0.250	0.500	0.534	0.394	0.628
	(11.11)***	-1.010	(6.27)***	(5.47)***	(2.99)**	-1.930
good health	0.235	3.273	0.411	0.182	0.076	0.323
	(2.76)**	(13.06)***	-1.850	-1.050	-0.540	-1.600
regular health	0.807	3.398	0.848	0.941	0.668	1.028
	(9.51)***	(13.38)***	(3.84)***	(5.63)***	(4.64)***	(4.83)***
poor health	1.471	4.035	1.584	1.720	1.194	1.852
	(14.17)***	(.)	(6.69)***	(8.47)***	(4.98)***	(4.87)***
really poor health	1.817	4.472	1.818	1.977	1.180	2.981
	(12.31)***	(11.76)***	(6.30)***	(6.28)***	(2.25)*	(6.78)***
_cons	-3.305	-6.264	-3.354	-3.316	-2.981	-3.552
	(-37.88)***	(-30.94)***	(-15.34)***	(-19.17)***	(-18.23)***	(-9.73)***
N	44820	5193	14076	11697	8020	5821

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1.A4 – Probability to be "on leave" and "quit doing some activity for health reasons" - Males

	male	(I) block 1	(II) block 2	(III) block 3	(IV) block 4	(V) block 5
formal workers	0.618	0.516	0.594	0.813	0.575	0.490
	(12.38)***	(3.46)***	(6.10)***	(7.41)***	(4.94)***	(2.21)*
good health	0.279	3.852	0.153	0.190	0.254	0.331
	(3.48)***	(21.00)***	-0.660	-1.310	-1.930	-1.710
regular health	0.960	4.132	0.939	0.798	0.930	1.212
	(12.00)***	(22.02)***	(4.23)***	(5.50)***	(7.01)***	(6.26)***
poor health	1.757	4.841	1.600	1.685	1.907	1.909
	(18.53)***	(.)	(6.60)***	(9.63)***	(11.27)***	(6.95)***
really poor health	1.820		0.971	1.957	2.212	2.379
	(11.69)***		(2.07)*	(6.64)***	(8.53)***	(4.65)***
_cons	-3.515	-6.654	-3.432	-3.568	-3.477	-3.544
	(-41.11)***	(-43.94)***	(-15.50)***	(-21.76)***	(-21.65)***	(-12.84)***
N	62164	4856	13461	16908	18126	8771

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Appendix Chapter 2

Table 2.A1 – Two-stage least squares estimates

	All Sample	Socioeconomic Index Quintile				
		(I)	(II)	(III)	(IV)	(V)
Child Labor						
Girls and Boys						
Log Family Income	-0.0275	0.0297	0.0808	0.0551	-0.0754	0.0734
	(-0.68)	-0.38	-0.87	-0.62	(-0.68)	-0.60
F-test first stage	29.541	9.209	5.881	7.308	3.365	2.661
Girls						
Log Family Income	-0.0402	0.0338	0.164	-0.0947	-0.0395	0.143
	(-0.73)	-0.32	-0.95	(-0.83)	(-0.29)	-1.16
F-test first stage	13.136	5.186	2.108	3.267	1.860	2.619
Boys						
Log Family Income	-0.0231	0.00441	0.0308	0.084	-0.107	0.189
	(-0.41)	-0.04	-0.30	-0.82	(-0.71)	-0.93
F-test first stage	17.231	5.148	5.143	6.124	2.139	1.203
Literacy						
Girls and Boys						
Log Family Income	0.0335	0.0623	-0.045	0.0732	0.0461	-0.0433
	-1.15	-1.23	(-0.62)	-1.03	-0.55	(-0.63)
F-test first stage	50.149	20.039	9.513	10.242	5.204	4.101
Girls						
Log Family Income	0.025	0.0677	-0.147	0.0442	-0.00763	-0.0402
	-0.6	-0.98	(-1.01)	-0.52	(-0.07)	(-0.56)
F-test first stage	24.341	11.328	2.584	5.928	2.697	3.729
Boys						
Log Family Income	0.0368	0.0418	-0.0146	0.162	0.111	0.0221
	-0.93	-0.62	(-0.19)	-1.78	-1.00	-0.18
F-test first stage	27.291	10.357	7.841	6.568	2.984	1.489
Attendance						
Girls and Boys						
Log Family Income	0.0973**	0.168**	0.119	0.0683	0.229*	-0.063
	-3.15	-2.92	-1.62	-0.90	-2.35	(-0.78)
F-test first stage	50.180	19.941	9.535	10.286	5.204	4.111
Girls						
Log Family Income	0.151***	0.228**	0.276	0.0324	0.242	-0.0262
	-3.40	-2.94	-1.92	-0.35	-1.82	(-0.31)
F-test first stage	24.335	11.298	2.576	5.923	2.697	3.729
Boys						
Log Family Income	0.0413	0.0915	0.0151	-0.0489	0.195	-0.0727
	-0.98	-1.17	-0.18	(-0.49)	-1.50	(-0.56)
F-test first stage	27.337	10.357	7.876	6.638	2.984	1.495

Instrumented: log family income

Instruments: post age_head educ_head gender_head age age^2 white female age_oldest educ_oldest family size, number of children in the family, T_k^j and T_k^j *post

Table 2.A2 – Testing Control Group

	child_labor	literacy	attendance
False Female Treatment	-0.00231	-0.0224	0.053
	-0.0167	-0.0132	(0.0139)***
False Male Treatment	-0.0331	0.0289	0.0339
	-0.0176	(0.0138)*	(0.0146)*
Pre-control Female	0.0208	-0.0303	0.0272
	-0.0148	(0.0113)**	(0.0121)*
Pre-control Male	-0.0135	0.0239	0.0624
	-0.0145	(0.0111)*	(0.0119)***
post	0.0914	0.0162	0.0859
	(0.0240)***	-0.0179	(0.0189)***
False Female Treatment x Post	0.00749	0.0275	-0.0357
	-0.0249	-0.0189	-0.0198
False Male Treatment x Post	0.0225	-0.0186	-0.0302
	-0.0248	-0.0189	-0.0198
Pre-control Female x Post	-0.0143	0.0424	-0.0135
	-0.0225	(0.0166)*	-0.0175
Pre-control Male x Post	-0.00752	0.00988	-0.0341
	-0.0213	-0.0159	(0.0167)*
N	13808	21158	21160
Prob > F	**child_labor**	**literacy**	**attendance**
Female			
False Treatment - Pre-control	0.295	0.352	*0.190*
Male			
False Treatment - Pre-control	0.193	0.096	0.833
Difference β4 - β5			
Female			
False Treatment - Pre-control	0.0218	-0.0149	-0.0222
Male			
False Treatment - Pre-control	0.0300	-0.0285	0.0039

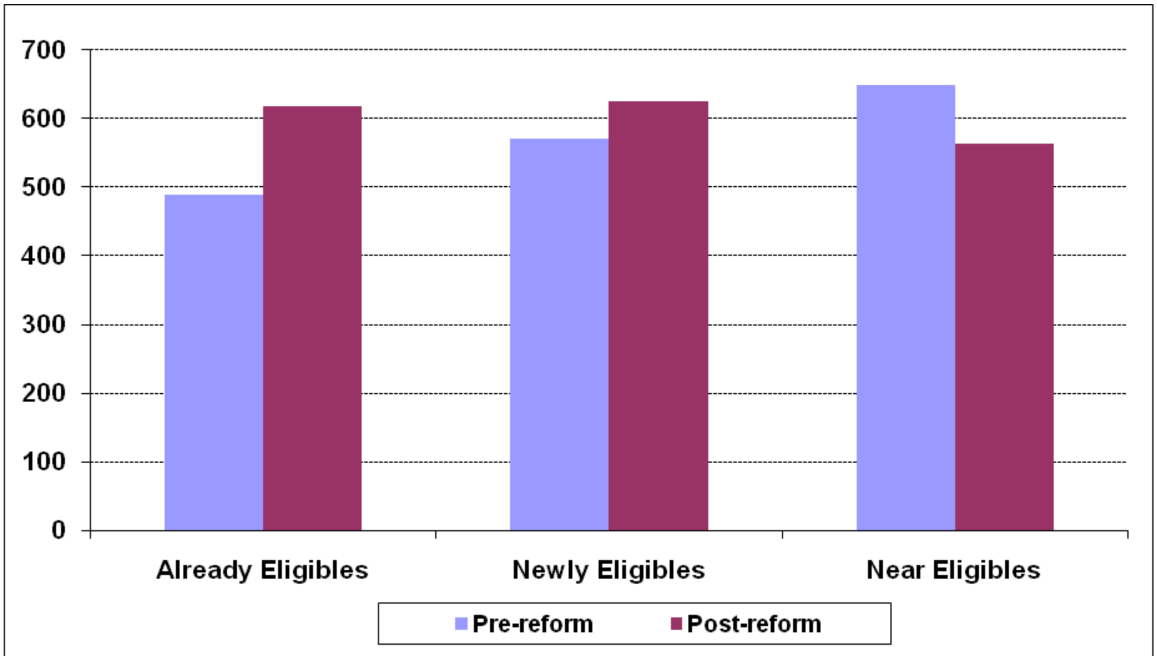
standar errors in parentheses
* p<0.05, **p<0.01, *** p<0.001

Table 2.A3 – Testing Female Bargaining Power

	Children living with Male Household Heads			Children living with Female Household Heads		
	coef.	robust std.err	P > t	coef.	robust std.err	P > t
Child Labor						
Female Treatment old rule x *Post*	0.035	0.025	0.158	-0.102	0.054	0.058
Male Treatment old rule x *Post*	-0.018	0.020	0.388	-0.147	0.152	0.332
Female Treatment new rule x *Post*	-0.035	0.022	0.108	-0.075	0.053	0.155
Male Treatment new rule x *Post*	-0.022	0.023	0.341	0.208	0.217	0.337
Literacy						
Female Treatment old rule x *Post*	-0.005	0.018	0.770	0.050	0.042	0.236
Male Treatment old rule x *Post*	0.038	0.015	0.013	-0.038	0.141	0.787
Female Treatment new rule x *Post*	0.012	0.017	0.473	0.050	0.041	0.224
Male Treatment new rule x *Post*	0.059	0.018	0.001	0.057	0.183	0.756
Attendance						
Female Treatment old rule x *Post*	0.003	0.019	0.865	0.140	0.043	0.001
Male Treatment old rule x *Post*	0.050	0.016	0.002	-0.271	0.096	0.005
Female Treatment new rule x *Post*	-0.020	0.018	0.276	0.095	0.043	0.026
Male Treatment new rule x *Post*	0.053	0.019	0.005	0.270	0.161	0.093
Girls						
Child Labor						
Female Treatment old rule x *Post*	0.000	0.032	0.998	-0.028	0.072	0.700
Male Treatment old rule x *Post*	0.012	0.027	0.657	-0.074	0.198	0.707
Female Treatment new rule x *Post*	-0.033	0.028	0.242	-0.059	0.073	0.418
Male Treatment new rule x *Post*	-0.011	0.030	0.703	0.483	0.279	0.084
Literacy						
Female Treatment old rule x *Post*	0.006	0.024	0.815	0.058	0.058	0.313
Male Treatment old rule x *Post*	0.033	0.021	0.126	-0.141	0.194	0.466
Female Treatment new rule x *Post*	-0.005	0.023	0.824	0.111	0.059	0.057
Male Treatment new rule x *Post*	0.069	0.025	0.005	0.115	0.255	0.653
Attendance						
Female Treatment old rule x *Post*	0.039	0.026	0.132	0.203	0.060	0.001
Male Treatment old rule x *Post*	0.061	0.023	0.008	-0.261	0.105	0.013
Female Treatment new rule x *Post*	-0.009	0.025	0.709	0.116	0.059	0.051
Male Treatment new rule x *Post*	0.044	0.027	0.100	0.374	0.199	0.061
Boys						
Child Labor						
Female Treatment old rule x *Post*	0.072	0.037	0.052	-0.185	0.081	0.023
Male Treatment old rule x *Post*	-0.043	0.031	0.157	-0.220	0.237	0.354
Female Treatment new rule x *Post*	-0.041	0.033	0.212	-0.083	0.077	0.282
Male Treatment new rule x *Post*	-0.032	0.034	0.351	-0.115	0.295	0.695
Literacy						
Female Treatment old rule x *Post*	-0.016	0.026	0.525	0.055	0.061	0.372
Male Treatment old rule x *Post*	0.041	0.022	0.055	0.038	0.197	0.846
Female Treatment new rule x *Post*	0.030	0.024	0.211	0.003	0.059	0.963
Male Treatment new rule x *Post*	0.051	0.025	0.042	-0.028	0.279	0.921
Attendance						
Female Treatment old rule x *Post*	-0.032	0.027	0.241	0.087	0.062	0.158
Male Treatment old rule x *Post*	0.041	0.023	0.076	-0.352	0.167	0.036
Female Treatment new rule x *Post*	-0.026	0.026	0.302	0.085	0.061	0.161
Male Treatment new rule x *Post*	0.062	0.027	0.019	0.108	0.215	0.617

Figure 2.A1 – Average Family Income

R$ (2002 values)



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